Multicausal systems ask for multicausal approaches: A network perspective on subjective well-being in individuals with autism spectrum disorder

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Abstract

Given the heterogeneity of autism spectrum disorder, an important limitation of much autism spectrum disorder research is that outcome measures are statistically modeled as separate dependent variables. Often, their multivariate structure is either ignored or treated as a nuisance. This study aims to lift this limitation by applying network analysis to explicate the multivariate pattern of risk and success factors for subjective well-being in autism spectrum disorder. We estimated a network structure for 27 potential factors in 2341 individuals with autism spectrum disorder to assess the centrality of specific life domains and their importance for well-being. The data included both self- and proxy-reported information. We identified *social satisfaction* and *societal contribution* as the strongest direct paths to subjective well-being. The results suggest that an important contribution to well-being lies in resources that allow the individual to engage in social relations, which influence well-being directly. Factors most important in determining the network's structure include self-reported *IQ, living situation, level of daily activity*, and *happiness. Number of family members with autism spectrum disorder* and *openness about one's diagnosis* are least important of all factors for subjective well-being. These types of results can serve as a roadmap for interventions directed at improving the well-being of individuals with autism spectrum disorder.

Since Leo Kanner's first account of autism as a distinct syndrome in 1943, extensive study of individuals with autism spectrum disorder (ASD) has shown the robustness of a well-established clinical phenomenon: the striking heterogeneity of this population in etiology and course of the disorder, with variable levels of positive outcome (Howlin et al., 2014). To accommodate this high level of heterogeneity, a broad range of interpretations, frameworks, and predictors of individual differences in outcome measures have been proposed, each bringing relevant and specific aspects of ASD into focus (Anderson et al., 2014; Burgess and Gutstein, 2007; Henninger and Taylor, 2013).

Research has yielded valuable results regarding the identification of predictors for positive outcome such as childhood IQ and early language ability (Gillespie-Lynch et al., 2012; Magiati et al., 2014). Recent studies, however, have also shown that, for example, IQ is necessary, but not sufficient for a positive outcome (Anderson et al., 2014; Howlin et al., 2004). Moreover, the predictive utility of IQ for positive outcome differs across various clinical samples (Chiang and Wineman, 2014; Renty and Roeyers, 2006; Van Heijst and Geurts, 2015), and it is unclear why. Thus, despite a large body of research identifying specific predictors of positive outcome, the predictive utility of such measures differs in unanticipated ways. In addition, the *mechanisms* by which these factors may influence outcome for individuals with ASD remain poorly understood. These results suggest that we need further understanding of how variations in the combination

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of risk and protective factors contribute to individual differences in later outcome.

One important limitation of research that may contribute to the limited success in understanding and predicting the course of ASD lies in the conceptualization and analysis of outcome measures. How positive outcome needs to be defined and analyzed is subject to debate, partly because of the heterogeneity in the antecedents and structure of such outcomes. In particular, the dominant focus of research has rested on specific outcome domains such as social functioning, education, IQ, and working conditions. However, it is well-established that most individuals with ASD do not meet criteria for "positive" outcome (Billstedt et al., 2005): few individuals with ASD have a large social network, are permanently employed, or are able to live independently (Howlin et al., 2004). But, being unemployed or having a small social network does not *necessarily* imply that an individual's subjective well-being is low: even in the presence of such limitations, there appear to be other person-specific factors (e.g. gender, language, physical problems) that, taken together, determine the course of the disorder in a complex pattern of interaction (Joseph et al., 2002; Miller and Tuchman, 2011; Volkmar et al., 1993).

It has, therefore, been suggested that we should conceptualize (positive) outcome taking the person–environment fit into account, that is, the interaction between stressors and supports and an individual's perception of competence and well-being (Ruble and Dalrymple, 1996). Importantly, this focus on interactions of single components that constitute subjective well-being enables us to study the construct as a multivariate system of mutually interacting factors. Typically, environmental factors and an individual's perception of competence and well-being are studied in isolation. That is, outcome measures are statistically modeled as separate dependent variables, and their multivariate structure is either ignored or treated as a nuisance. In addition, while researchers have conducted numerous studies aimed at elucidating specific interactions and effects, there are very few examples of the application of a multivariate approach to unravel crucial determinants for later outcome (e.g. Woodman et al., 2016). No study, however, has provided a multivariate overview of these factors' interrelations. This study aims to lift this limitation, by utilizing novel network analysis techniques to explicate and study the multifactorial (and likely multicausal) structure of outcome. Also, subjective and objective evaluations of outcome reflect very distinct types of information (Ruggeri et al., 2001). In this study, we focus on an individual's evaluation of different life domains in relation to both subjective and objective measures. A focus on only objective information about outcome would likely lead to a different pattern of results. Hence, using a system-level approach in the study of the person–environment system, we aim to provide an overview of the multitude of factors in people's lives, such as having family members with ASD or having physical problems, that have an impact on their *subjective* well-being and other aspects of outcome. Recent literature has also highlighted the need to accommodate the multifactorial nature of antecedents of subjective well-being in ASD populations, as it is unlikely that there could be a single element of ASD that predicts well-being in all cases (Burgess and Gutstein, 2007; De Vries and Geurts, 2015).

In this study, we use a network approach to psychopathology (Borsboom and Cramer, 2013; Cramer et al., 2010) where disorders are conceptualized in terms of systems of interacting factors, which may involve variables classically viewed as "symptoms." The network architecture that characterizes a person determines the possible states in which these functionally interrelated factors may settle (Cramer et al., 2012). Combined with novel measurement procedures and statistical technology, network approaches have provided new psychometric tools suited to study the complex dynamics of psychological constructs. Here, we use these tools to study the architecture of complex interrelations within a multivariate system of predictors that make up person–environment fit for the ASD population. Our aim is to provide a clear overview of the multitude of factors that have an impact on subjective well-being and other outcome domains. To this end, we simultaneously study both subjective and objective variables in a large sample of individuals with ASD (N = 2341) by applying network analysis techniques in an exploratory fashion. We examine what variables define a (good) person–environment fit for individuals with ASD and how psychological, environmental, and medical factors relate to their subjective well-being. Subjective well-being can be assessed with distinct concepts reflecting the affective and cognitive evaluation of one's life (Bartels and Boomsma, 2009). In this regard, we focus on individuals' evaluation of their average state of happiness in life and use this subjective non-temporary affective appraisal of their lives as a representation of subjective well-being.

The structure of this article is as follows. First, we construct a correlation network of our sample in order to get a first impression of the architecture of interrelations. Second, we will construct a tentative causal architecture of the investigated variables, by combining partial correlation networks with penalized estimation procedures suited to control type I error rates (Friedman et al., 2010). With this approach, we can create parsimonious networks that reveal the most stable relations among the variables (Costantini et al., 2014). Finally, the important characteristics of the resulting network will be evaluated by the analysis of so-called centrality measures, which yield information about the importance of different factors in the network.

Table 1. Descriptives for the participants (N = 2341).

Variable	Mean (SD)	Range
Age (years)	32.02 (15.02)	16–91
Age of diagnosis (years)	20.76 (17.02)	0–74
Gender	72% male	
	28% female	
Clinical diagnosis		
Autism	N = 393	
Asperger's syndrome	N = 909	
PDD-NOS	N = 874	
ASD	N = 165	

SD: standard deviation; PDD-NOS: pervasive developmental disorder—not otherwise specified; ASD: autism spectrum disorder.

Method

Participants

This study is based on data[1] from the Dutch Association for Autism (Nederlandse Vereniging voor Autisme, NVA) and the VU University Amsterdam (VU) obtained with an online questionnaire. A total of 3521 Dutch participants aged 2–90 years were recruited through the NVA member register and online distribution of the questionnaire. For this study, we focused on participants aged older than 16 years. This choice was motivated by the selection of life domains included in this study: some of the questions were explicitly work-related and as such less applicable to participants younger than 16 years. In total, 2341 questionnaires were completed by or about individuals who were 16 years and older (for descriptives, see Table 1).

Measures

The NVA study was originally designed to assess a broad spectrum of domains within the Dutch ASD population, ranging from questions about an individual's environment to subjective questions about one's well-being and attitude toward activities organized by the NVA. We selected a set of 27 questions to obtain a wide range of life domains, covering demographics, diagnosis, treatment, education, living situation, happiness and well-being, work, social contact, and societal contribution. Hence, we excluded all questions directed at the evaluation of NVA-related activities, future demands for care, and detailed family information (90% of all (257) questions). Note that our set of questions included *self-reported* (1) evaluation measures, such as their social satisfaction; (2) demographic measures, such as their age and IQ; and (3) medical and environmental measures, such as the number of comorbidities they have. In Table 2, all measures are explained including respective recoding and abbreviation in the network.

Subjective evaluation measures. Subjective measures, such as happiness and the four satisfaction questions (advice satisfaction, care satisfaction, social satisfaction, and treatment satisfaction), were rated on a scale from 1 (*not at all*) to 5 (*very much*) (e.g. How satisfied are you about the care you have received?). The level of success was rated on a scale from 1 (*not at all*) to 10 (*very much*) and the feeling that one can contribute sufficiently to society was indicated by either 1 (*yes*), 2 (*to some extent*), or 3 (*no*). For the latter, scores were reverse coded so that higher scores reflected more societal contribution.

Subjective demographic measures. Participants were asked to report their age, gender, their age of diagnosis, diagnosis, and their IQ score.

Medical and environmental measures. For most of the other measures, such as social contacts, physical problems, and comorbidity, participants selected the *type of* social contacts, physical problems, or comorbid disorders (e.g. which type of physical problems do you experience? which comorbid disorders do you have?). These measures present a problem for the current statistical analyses, because if all listed problems and disorders are treated as distinct variables, the dimensionality of the data becomes so large that it hampers estimation and makes the interpretation of results more difficult. To cope with this problem, we computed count measures, based on these originally nominal variables. That is, most non-subjective measures in the network are aggregated nominal variables and reflect a total number, for example, the *number of* physical problems an individual reports, rather than the specific type of problems listed.[2]

Analysis

Networks generally represent a selection of elements (e.g. symptoms or questionnaire items) that are visualized as nodes. These nodes are connected by edges. In the statistical networks used here, edges typically represent a statistical measure of association—for instance, a correlation, partial correlation, or estimated causal effect. In the visual representation of networks, positive associations are typically represented as green edges, while negative associations are represented as red edges. The strength of the association is visualized through the thickness of the edge: the stronger the association, the thicker the edge. In the visualizations used here, nodes that have many strong associations are positioned near the center of the network, while nodes with weaker correlations are positioned in the periphery of the network (Fruchterman and Reingold, 1991).

We computed two types of networks using the R-package *qgraph* (Epskamp et al., 2012, version 1.3): an *association* network and three *concentration* networks.

Table 2. Detailed legend for Figures 1 and 2.

Abbreviation	Meaning in the network	Original question	Scale in questionnaire	Scale in network
advS	Satisfaction about given advice	How satisfied are you about the advice you received considering … x …?	11 Questions Ordinal (A)	Ordinal (6-point scale)
age	Age	What is your year of birth?	Continuous	Continuous
ageD	Age of diagnosis	How old were you when you were diagnosed?	Continuous	Continuous
carI	No. of care indications	Have you received a care indication for … x …?	12 Questions Binary (A)	Ordinal
carS	Satisfaction about received care	How satisfied are you about care you received regarding … x …?	6 Questions Ordinal (A)	Ordinal (6-point scale)
cha	No. of strong characteristics	Which of the strong characteristics listed below do you posses because of ASD?	11 Response options Nominal (A)	Ordinal
com	No. of co-occurring diagnoses	Which of the co-occurring diagnoses listed below do you have?	25 Response options Nominal (A)	Ordinal
con	Societal contribution	Do you feel that you can contribute to society?	Ordinal	Ordinal (3-point scale)
edU	No. of unfinished education	Which of the educational programs listed below have you started but not completed?	17 Response options Nominal (A)	Ordinal
dly	Level of daily activity	What option/s listed below resemble/your daily activity the most?	12 Response options Nominal (A)	Ordinal (4-point scale)
dlyH	No. of daily activity hours	How many hours do you spend on daily activity … x …?	12 Questions Continuous	Continuous
fam	No. family members with ASD	Please indicate whether one of the listed family members also has an ASD diagnosis.	14 Response options Nominal (A)	Ordinal
gen	Gender (1) Male (2) Female	What is your gender?	Binary	Binary
hap	Happy	How happy are you?	Ordinal	Ordinal (6-point scale)
inf	Informant (1) Other (2) Self		Binary	Binary
int	No. of interests	Which type of specific interest do you currently have?	16 Response options Nominal (A)	Ordinal
iq	IQ	What is your IQ score?	Continuous	Continuous
liv	(1) Supervised (2) Unsupervised living	Which of the listed options resemble your living situation the most?	5 Response options Nominal (A)	Binary
med	No. of medication one has used	Which of the medication types listed below have you received?	16 Response options Nominal (A)	Ordinal
phy	No. of physical problems	Which of the physical problems listed below do you currently experience?	7 Response options Nominal (A)	Ordinal
soc	No. of social contacts	Which of the social contacts listed below do you have?	13 Response options Nominal (A)	Ordinal
socS	Satisfaction about social contacts	How satisfied are you generally about you social contacts?	Ordinal	Ordinal (6-point scale)
suc	Successful	Please indicate how successful you consider yourself?	Ordinal	Ordinal (3-point scale)
tolD	Open about diagnosis (1) No (2) Yes	Did you tell people at work about your diagnosis?	Binary	Binary
tra	No. of problematic transition periods in life	Did you experience any of problems during transitional periods in life listed below?	8 Response options Nominal (A)	Ordinal
tre	No. of received treatments	Which of the treatments listed below did you receive?	40 Response options Nominal (A)	Ordinal
treS	Satisfaction about received treatments	How satisfied were you about treatment … x …?	40 Questions Ordinal (A)	Ordinal (6-point scale)

ASD: autism spectrum disorder.
If we aggregated the question in the presented networks, we indicated this with the letter (A) in the *scale in questionnaire* column.

The association network is a weighted but undirected network in which the edges represent the *correlation* between the variables. We excluded correlations falling below r = 0.10 from the visual representation (these correlations are included in the network analyses). Correlation networks provide an insightful initial overview of the interrelations between all factors relevant to subjective well-being, but are inherently ambiguous with respect to causal relations (Borsboom and Cramer, 2013). That is, correlation networks generally show a high rate of spurious associations between nodes (false positives) that may, for instance, arise when two nodes share common dependence on a third. To gain more insights regarding the causal structure of the system, we, therefore, computed concentration networks in which edges represent partial correlations, that is, the correlation between two elements that arises while controlling statistically for all other elements in the network. The architecture of partial correlation networks is commonly used as a first approximation of the causal architecture of a system, that is, it encodes plausible pathways through which the changes in the network structure may propagate, without a priori assuming a particular directionality of this propagation of such changes.

To estimate the unknown graph structure, that is, the set of pairwise associations of this study's set of variables, we computed three concentration networks: (1) a basic partial correlation network, (2) a thresholded partial correlation network using Holm–Bonferroni correction, and (3) a partial correlation network using a graphical *least absolute shrinkage and selection operator* (lasso; Friedman et al., 2010; Tibshirani, 1996). In other words, the network structure is identified by the application of state-of-the-art statistical methodology for solving high-dimensional regression problems (based on penalized regression; Meinshausen and Bühlmann, 2006; Tibshirani, 1996). The *lasso* method both controls type I error rates and facilitates in interpretation because it only retains the most robust edges in the concentration network. Due to the penalization used in the *lasso*, if an edge is present in the graphical *lasso* network, one can be fairly sure that this association is a structural element of the network architecture because the method has very high specificity; however, the sensitivity of the *lasso* method is considerably smaller, so the concentration networks we present are likely to miss a possibly sizeable percentage of weaker edges that cannot be estimated with sufficient precision to include them in the graph (Van Borkulo et al., 2014). Thus, one can think of the *lasso* concentration graph presented here as an accurate estimate of the overall architecture of the network, but has to keep in mind that although the relations visualized are the strongest and most precisely estimated relations, they do not strictly exhaust the connections in the system.

The created networks then allow for the identification of influential focal points of the network through the analysis of *node centrality* indices: *betweenness, closeness*, and *strength*. These subsequent analyses of the network structure use network analysis techniques taken from the emerging methodological tools of complex networks science (Barabási, 2011; Kolaczyk and Csardi 2009; Newman, 2010) to determine the centrality of variables in the network (for a statistical definition, see Opsahl et al., 2010). We represent these measures in centrality plots in Supplementary Figure A2 that depict centrality indices for all variables in all concentration networks. Network centrality is a metric that indicates the overall connectivity of a variable in the network and has gained substantial attention in recent clinical literature (Robinaugh et al., 2014, Wigman et al., 2015). In a weighted network, the *strength* of a node simply equals the sum of all its direct connections. Node *betweenness* indicates how often a node lies on the shortest path between two randomly chosen other nodes in the graph. Node *closeness* quantifies the average distance between this node and all other nodes in the network (for a more elaborate definition of these concepts, see Costantini et al., 2014).
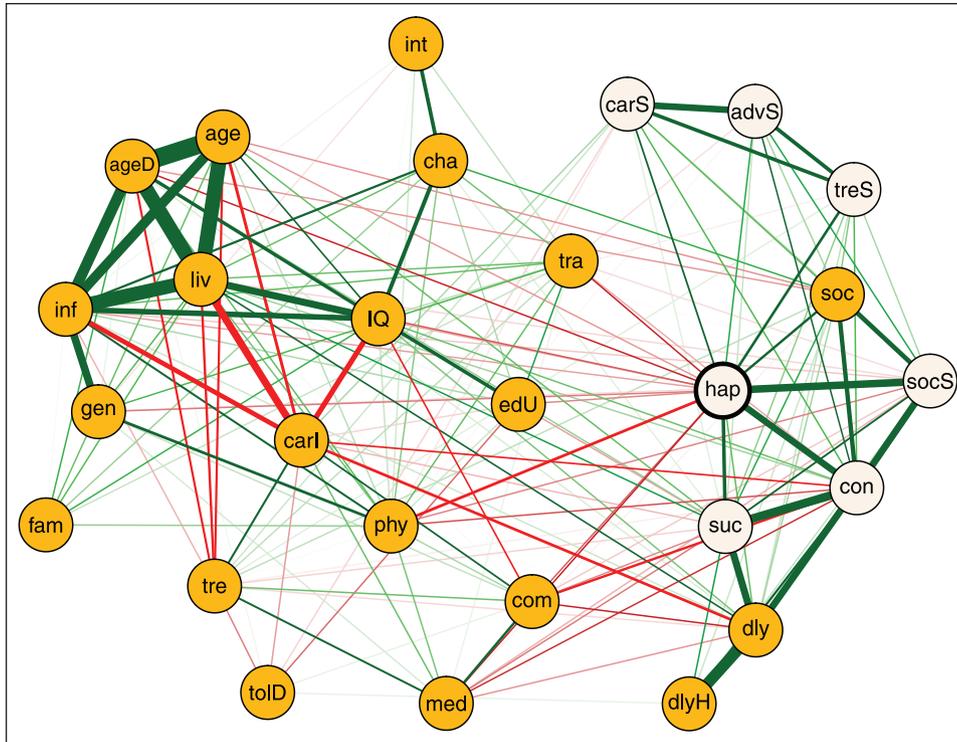
Results

Sample characteristics

Even though all participants were allowed to fill in the questionnaires themselves, the majority of the questionnaires was taken by parents (or legitimate representatives) of the person with ASD (67.6%). The remaining questionnaires were based on self-report of the person with ASD (32.4%). With about 39% females, this sample has an overrepresentation of females with ASD compared to the gender ratio in other referred clinical samples (Lord et al., 1982). A majority (85%) of the participants reported an IQ score in the normal range (>70 and <130) and a relatively high percentage (14%) reported an IQ score higher than 130. All participants were Dutch and met criteria for one of the following clinical diagnoses according to the *Diagnostic and Statistical Manual of Mental Disorders* (4th ed.; DSM-IV; APA, 1994): classical autism (autistic disorder) (17%), Asperger's syndrome, and (38%), pervasive developmental disorder—not otherwise specified (PDD-NOS) (38%). However, although the *Diagnostic and Statistical Manual of Mental Disorders* (5th ed.; DSM-5) was not officially introduced, 7% of the participants reported the DSM-5 diagnosis *ASD* (see also Table 1). Note that we computed all networks employing pairwise deletion of missing data. In the data we used in the analysis, missing data percentages ranged from 0% to 59.5% (openness about one's diagnosis) with M = 17.5, standard deviation (SD) = 27.

Subjective well-being networks

In the figures depicting the networks and centrality plots, we use the abbreviations as shown in Table 2. The color of the node refers to the type of question: the white nodes

Figure 1. Highlighted graphical *lasso* network for individuals with ASD (this graph without highlights can be found in Supplementary Figure A1). For reasons of clarity and comprehensibility, we have highlighted the nodes and edges we discuss most in the result section. Positive associations are represented as green edges in the network, while negative associations are represented as red edges.

reflect subjective questions directed at an individual's perception of his or her condition, while the yellow nodes reflect objective questions about an individual's environment and situation. We examined which factors define a (good) person–environment fit for individuals with ASD and how this relates to happiness.

The association network. With the created association network, one gets a first impression of the pattern of correlations that characterize subjective well-being and related factors. We found that *social satisfaction* (*socS*) and *societal contribution* (*con*) were the strongest direct paths to *happiness*, followed by *feeling successful* (*suc*) and *treatment satisfaction* (*treS*). Simultaneously, more *physical problems* (*phy*) were associated with less reported *happiness* (*hap*).

In addition, this association network featured a highly connected cluster of non-subjective factors, which suggests that participants with a diagnosis later in life are more likely to live independently, have a higher self-reported IQ, and fewer care indications. They were also more likely to fill out this questionnaire themselves. This cluster might characterize the less severe cases who are able to lead a relatively more stable and independent life.

The concentration network. The *lasso* concentration network is represented in Figure 1. Many associations apparent in the association network remain apparent in the concentration network. Notably, mainly subjective questions are directly related to happiness: *social satisfaction, feeling able to contribute to society*, and *treatment satisfaction* show strong enhancing relations with feeling happy. An especially strong connection was found between social satisfaction and feeling happy. Importantly, it appears that the *number of social contacts* does not directly relate to feeling happy, but influences happiness through social satisfaction. The only objective factor that directly influences happiness is the *number of physical problems* a person reports.

Specifically, the cluster of the majority of non-subjective factors is connected to happiness through *number of physical problems* and *number of social contacts*. This suggests that these variables may act as important gateways from stressors and supports to subjective well-being. The structure of these factors' interrelations (yellow nodes in the networks) affirms the presence of the connections found in the association network (see Figure 2). However, the factors identified as weakly connected in the association network do not show up in the multivariate concentration network anymore: *having family members with ASD, openness about one's diagnosis*, and the cluster of *number of received treatments, number of used medication*, and *number of co-occurring diagnoses* are not associated with the rest of the fitted network. This may indicate that the effects of such variables are largely indirect, although we cannot rule out the possibility that some of the vanishing

Figure 2. Association network for individuals with ASD. The color of the node refers to the type of question: the white nodes reflect subjective questions directed at an individual's perception while the yellow nodes reflect more or less objective questions about an individual's environment and situation. Positive associations are represented as green edges in the network, while negative associations are represented as red edges.

relations may be due to the lower sensitivity of the *lasso* estimates used for the concentration network.

The concentration networks reveal several other interesting phenomena of potential importance. First, female participants seem to suffer from more physical problems and are more likely to fill in the questionnaire themselves suggesting a somewhat higher level of functioning. Second, individuals with higher self-reported scores are more likely to (1) have a higher number of unfinished educational programs, (2) report more challenging transition periods in their lives, and (3) report more good characteristics *because* of their ASD. Self-reported IQ appears to influence well-being indirectly, via the number of strong characteristics (*cha*) people attribute to themselves, which might allow them to engage in social relations (*soc*); thus, in this structure, IQ might play the role of a resource that allows individuals to develop skills that facilitate social functioning. Third, effects of the *number* of social contacts are mediated through the *satisfaction* about social contacts, suggesting that when it comes to social contacts in ASD, quality trumps quantity.

Centrality plots for the concentration networks are depicted in Supplementary Figure A2, where we also included the *thresholded* network's centrality indices. With these thresholded network indices, we correct for multiple comparisons as associations between the factors

were accepted as statistically significant only after the Holm–Bonferroni correction.

Factors having the highest centrality levels in the networks include self-reported *IQ, living situation, level of daily activity*, and *happiness*. Focusing on the sparse *lasso* concentration network centralities, the central importance of self-reported *IQ* and *happiness* as key variables in the network is corroborated. Also, *living situation* ranks among the most central factors in the *lasso* network. On the other hand, we find that *number of family members with ASD* and *openness about one's ASD diagnosis* have the lowest centrality on all indices (betweenness, closeness, and strength) of all factors in the *lasso* network. This implies that those factors do not play an important role in the constitution of the network structure: they do not funnel the mutual influence of other factors in the network and they are not (strongly) connected to the rest of the network.[3]

In addition, we conducted a comparative network analysis to examine whether self- versus proxy report lead to substantively different main effects. To examine whether the network structure found in the original sample (N=2341) of this study differed substantively from the network structure of either the proxy report sample (N=1583) or the self-report sample (N=758), we created graphical lasso networks splitting the data regarding self- or proxy report. We compared these networks by correlating shortest

path lengths across graphs. The resulting correlation between the original network and the proxy report sample (r=0.90) and the original network and the self-report sample (r=0.68) suggest that the networks do not differ substantively.

Discussion[4]

This article is the first to represent and analyze the multivariate network structure of factors involved in well-being in people with ASD. Some findings conform well with the literature on risk and success factors for well-being in ASD populations, whereas other findings point to unexpected characteristics of the multivariate pattern of interrelations, such as associations between factors that are much more pronounced or surprisingly absent. We summarize core findings of this study, providing a first insight in the network structure of factors relevant to subjective well-being and positive outcome in individuals with ASD.

First, self-reported *IQ* and *happiness* emerged as highly central factors that often act as a bridge along the shortest path between two other nodes in the network. This implies that they are highly connected focal points that can funnel and influence the associations of factors in the network more than others. This finding is in line with the results of many well-being studies in ASD populations: IQ is an influential positive predictor for outcome and well-being (Magiati et al., 2014). Yet, the central prominence of the subjective evaluation of happiness in the network stresses the importance of including subjective well-being in the framework of outcome evaluation in ASD populations. Unfortunately, earlier studies tended to focus on one-dimensional outcome domains, such as academic success, where their interrelation with subjective well-being was not taken into account (Billstedt et al., 2011). In the network structure, self-reported IQ appears connected to well-being indirectly via a path that involves strong characteristics and social relations, which suggests that, in ASD, its most important contribution to well-being might lie in acting as a resource that allows the individual to engage in social relations and adaptive functioning, which influence well-being directly.

Second, social satisfaction emerges as highly important for subjective well-being. Importantly, the number of social contacts from different contexts (such as family, work, leisure activities) does not influence subjective well-being directly, but merely through one's satisfaction with these contacts. This is in line with the well-established notion that the importance of the social aspect of life is derived largely from the social satisfaction's direct influence on an individual's subjective well-being (Pinquart and Sörensen, 2000). Recent literature has shown that people with ASD feel more lonely (White and Roberson-Nay, 2009) and experience their social contacts as less satisfactory (Bauminger et al., 2010; Stokes et al., 2007; Whitehouse et al., 2009). This is also in line with studies that have shown that the lack of social responsiveness and adaptive behaviors partly explain low reported well-being scores of children with ASD (Kuhlthau et al., 2010). These results might suggest that interventions focusing on social functioning for people with ASD should focus on improving their subjective evaluation of the existing social relationships and social contact.

Third, the results showed that the number of physical problems that people with ASD report represents the strongest risk factor for their subjective well-being. This is in line with findings in the ASD population suggesting that pain and physical stress act as a setting event for problem behavior that, in turn, influences an individual's level of well-being (Walsh et al., 2013). Also, recent studies have shown a high prevalence of unnoticed medical problems in adults with ASD and increased rates of mortality in adults with ASD when having low IQ test scores (<85) (Kats et al., 2013; Maenner et al., 2015). It is suggested that ASD symptoms, such as social problems, may increase the risk of medical problems to remain untreated over time. Caregivers may not be skilled to recognize those in the ASD population and are thus unable to provide effective prevention and intervention. In the context of these findings, our result underlines the need for further research on detecting physical problems in individuals with ASD.

Fourth, our results suggest that having family members with ASD and openness about one's ASD diagnosis do not relate to any other factor in the network. This is of interest because it is often suggested that having siblings or parents with Broad Autism Phenotype features relates to more behavioral problems and more problematic family relationships (Ingersoll and Hambrick, 2011; Messinger et al., 2013; Petalas et al., 2012). Future research could add more detailed information to the network, such as specific behavioral problems related to ASD, and examine whether having family members with ASD might influence risk and protective factors in the network only for a specific set of problems and not for others. Also, there is a chain of *number of treatments, number of medication*, and *number of co-occurring disorders* in the presented *lasso* network that is not connected to the rest of the network. However, one should be careful in overinterpreting absent connections in the graph, as these may be due to limited power and may at least partly result from the way the relevant variables are defined; unpacking the variables in terms of their constituent medications and diagnoses will yield a more connected network (see Supplementary Appendix). Because the current sample size does not admit detailed interpretation of this large network, future research is required to study medication- and diagnosis-specific patterns of associations related to well-being.

To our knowledge, this study is the first attempt to elucidate the multivariate system of subjective well-being in the ASD population using network techniques. Our article illustrates how the application of this approach can illuminate the association pattern of risk and success factors for

subjective well-being of people with ASD. In addition, our results point to urgent targets and focal points for intervention by identifying highly central factors that make up the person–environment system.

Limitations and future directions

Some limitations to our findings should be considered. First, although the selected set of variables was intended to provide a comprehensive list of factors operative in the multicausal system of subjective well-being and outcome, decisions about which factors to include were restricted by the available data. Consequently, our networks do not represent the *in-depth* network of risk and success factors relevant to subjective well-being and outcome in this population. Important factors that should be included in future work are, for example, specific ASD strengths and deficits, such as hyper-attention to detail or social impairment. Nonetheless, our results provide first insights that can guide future research aimed at clarifying how these risk and success factors influence subjective well-being and outcome in the ASD population.

Second, the networks are based on data that include both self-report information and proxy report information. Recent literature suggests that there may be a substantive discrepancy between the reports of parents and their (adolescent) children with ASD on quality-of-life measures (Ikeda et al., 2014; Sheldrick et al., 2012). However, this bias seems to some extent inevitable for samples including cognitively impaired individuals who cannot fill in questionnaires themselves. Recent literature suggests that future research should rephrase questions for parent proxy report, explicitly asking to report the child's quality of life, as they believe their children would (Sheldrick et al., 2012). In order to check whether this influences the main results we report, we included the informant (self or proxy) as a node (*inf*) in the network. Here, we could conclude that the informant filling in the questionnaire is only associated with the cluster of objective variables, such as gender, age of diagnosis, and living situation, and does not influence the reported results. In addition, the results of our comparative analysis for the proxy report sample and the self-report sample suggest a similar pattern of relationships among the primary variables. The somewhat higher correlation we found for the proxy report sample can be explained by the configuration of the original sample: it consisted of 67.6% proxy report information and 32.4% self-report information. Moreover, when interpreting the main effects of these two separate networks, the conclusions we can draw are highly similar to the conclusions based on the combined network.

Third, and related to our second limitation, our questionnaire was distributed through the NVA member register and our sample might thus be biased. On one hand, this distribution channel enabled us to assess the full range of IQ levels, as both parents of people with ASD and people with ASD themselves could fill in the questionnaire. On the other hand, this has led to some factors that hinder the representativity of the current sample. There was an overrepresentation of females in our sample, which is a well-known and often reported bias in online surveys on health issues (Licciardone et al., 2001; Smith, 2008). Also, there might be an overrepresentation of people with ASD who reported an especially high IQ score above 130 (14%).

Fourth, participants were asked to report their IQ score, which produces a less reliable estimate of intelligence than a valid assessment would (Paulhus et al., 1998). We were limited by the online survey context, resulting in an inability to verify the reported IQ of participants. It would, therefore, be good to replicate these findings implementing a standardized assessment of intelligence. The limitations listed above show that the data of this study have strengths and weaknesses, so the findings of this study cannot be directly compared with epidemiological studies.

Fifth, the question of when to combine items in one node in the network instead of keeping them separately remains a cutting-edge issue in many field of network science. In the absence of definitive work on topological overlap (Costantini et al., 2014) for psychological variables, we have to make some assumptions about them. However, particularly when interested in how certain variables influence different aspects of subjective well-being, studying individual aspects of psychological constructs promises important insights (Fried et al., 2014; Lux and Kendler, 2010). In this study, we thought it reasonable to model all well-being variables separately, which is confirmed by the moderate, but not high, partial correlations between these variables in the network.

Despite these limitations, our findings provide a first mapping of the network structure of risk and success factors relevant to subjective well-being and outcome in individuals with ASD. We have shown that the network approach to psychopathology can be profitably used to study the multivariate pattern of associations constitutive of subjective well-being in the ASD population. The inferred networks offer a roadmap of paths that can lead to good subjective well-being. Future research in this area may use the presented techniques for longitudinal data: how does the multivariate system of risk and success factors change over time (Bringmann et al., 2014)? How do the central factors in the network behave? Recent technological advances offer unparalleled opportunities to gather data on complex systems which enable us to translate large amounts of collected data into informative individual networks that could improve monitoring and intervention for well-being of individuals with an ASD diagnosis.

Declaration of conflicting interests

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Notes

1. These data have been previously used in a national report (Begeer et al., 2013); however, the network structure of the used measures had not yet been analyzed in the manner of this study.

2. To check whether this step affected the results, we compared the network with aggregated nominal variables to a disaggregated network, in which each nominal variable is a separate node, by correlating shortest path lengths across graphs. The resulting correlation ($r = 0.93$) suggests that aggregated and disaggregated networks do not differ substantively in terms of the main effects we report. Thus, to facilitate interpretation, we report only the aggregated network in the main text. The disaggregated network visualization can be found in Supplementary Figure A3.

3. A small part of our sample filled in the Autism Quotient (Hoekstra et al., 2008) in a second assessment. To check whether the network structure found in the original sample ($N = 2341$) differed from this smaller sample ($N = 385$) in which we could verify the diagnosis, we compared the networks by correlating shortest path lengths across graphs. The resulting correlation ($r = 0.78$) suggests that the samples do not differ substantively in terms of the main effects we report.

4. To confirm the importance of the reported results, we evaluated this article with the help of a feedback panel consisting of people with ASD and professionals working with people with ASD.

References

American Psychiatric Association (APA) (1994) *Diagnostic and Statistical Manual of Mental Disorders*. 4th ed. Arlington, VA: American Psychiatric Publishing.

Anderson DK, Liang JW and Lord C (2014) Predicting young adult outcome among more and less cognitively able individuals with autism spectrum disorders. *Journal of Child Psychology and Psychiatry* 55: 485–494.

Barabási AL, Gulbahce N and Loscalzo J (2011) Network medicine: A network-based approach to human disease. *Nature Reviews Genetics* 12(1): 56–68.

Bartels M and Boomsma DI (2009) Born to be happy? The etiology of subjective well-being. *Behavior Genetics* 39: 605–615.

Bauminger N, Solomon M and Rogers SJ (2010) Externalizing and internalizing behaviors in ASD. *Autism Research* 3: 101–112.

Begeer S, Wierda M and Venderbosch S (2013) *Allemaal Autisme, Allemaal Anders*. De Bilt: Nederlandse Vereniging voor Autisme.

Billstedt E, Gillberg C and Gillberg C (2005) Autism after adolescence: population-based 13- to 22-year follow-up study of 120 individuals with autism diagnosed in childhood. *Journal of Autism and Developmental Disorders* 35: 351–360.

Billstedt E, Gillberg IC and Gillberg C (2011) Aspects of quality of life in adults diagnosed with autism in childhood: A population-based study. *Autism* 15: 7–20.

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

Bringmann LF, Lemmens LHJM, Huibers MJH, et al. (2014) Revealing the dynamic network structure of the Beck Depression Inventory-II. *Psychological Medicine* 45: 747–757.

Burgess AF and Gutstein SE (2007) Quality of life for people with autism: Raising the standard for evaluating successful outcomes. *Child and Adolescent Mental Health* 12: 80–86.

Chiang HM and Wineman I (2014) Factors associated with quality of life in individuals with autism spectrum disorders: A review of literature. *Research in Autism Spectrum Disorders* 8: 974–986.

Costantini G, Epskamp S, Borsboom D, et al. (2014) State of the aRt personality research: A tutorial on network analysis of personality data in R. *Journal of Research in Personality* 54: 13–29.

Cramer AOJ, Van der Sluis S, Noordhof A, et al. (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: 414–431.

Cramer AOJ, Waldorp LJ, Van der Maas HL, et al. (2010) Comorbidity: A network perspective. *Behavioral and Brain Sciences* 33: 137–150.

De Vries M and Geurts HM (2015) Influence of autism traits and executive functioning on quality of life in children with an autism spectrum disorder. *Journal of Autism and Developmental Disorders* 45(9): 2734–2743.

Epskamp S, Cramer AOJ, Waldorp LJ, et al. (2012) Qgraph: network visualizations of relationships in psychometric data. *Journal of Statistical Software* 48: 1–18.

Fried EI, Nesse RM, Zivin K, et al. (2014) Depression is more than the sum score of its parts: Individual DSM symptoms have different risk factors. *Psychological Medicine* 44(10): 2067–2076.

Friedman J, Hastie T and Tibshirani R (2010) Regularization paths for generalized linear models via coordinate descent. *Journal of Statistical Software* 33: 1–22.

Fruchterman TM and Reingold EM (1991) Graph drawing by force-directed placement. *Software: Practice & Experience* 21: 1129–1164.

Gillespie-Lynch K, Sepeta L, Wang Y, et al. (2012) Early childhood predictors of the social competence of adults with autism. *Journal of Autism and Developmental Disorders* 42: 161–174.

Henninger NA and Taylor JL (2013) Outcomes in adults with autism spectrum disorders: A historical perspective. *Autism* 17: 103–116.

Hoekstra RA, Bartels M, Cath DC, et al. (2008) Factor structure, reliability and criterion validity of the Autism-Spectrum

Quotient (AQ): A study in Dutch population and patient groups. *Journal of Autism and Developmental Disorders* 38(8): 1555–1566.

Howlin P, Goode S, Hutton J, et al. (2004) Adult outcome for children with autism. *Journal of Child Psychology and Psychiatry* 45: 212–229.

Howlin P, Savage S, Moss P, et al. (2014) Cognitive and language skills in adults with autism: A 40-year follow-up. *Journal of Child Psychology and Psychiatry* 55: 49–58.

Ikeda E, Hinckson E and Krägeloh C (2014) Assessment of quality of life in children and youth with autism spectrum disorder: A critical review. *Quality of Life Research* 23: 1069–1085.

Ingersoll B and Hambrick DZ (2011) The relationship between the broader autism phenotype, child severity, and stress and depression in parents of children with autism spectrum disorders. *Research in Autism Spectrum Disorders* 5: 337–344.

Joseph RM, Tager-Flusberg H and Lord C (2002) Cognitive profiles and social-communicative functioning in children with autism spectrum disorder. *Journal of Child Psychology and Psychiatry* 43: 807–821.

Kats D, Payne L, Parlier M, et al. (2013) Prevalence of selected clinical problems in older adults with autism and intellectual disability. *Journal of Neurodevelopmental Disorders* 5: 27.

Kolaczyk ED and Csárdi G (2014) *Statistical Analysis of Network Data with R*, vol. 65. Springer.

Kuhlthau K, Orlich F, Hall TA, et al. (2010) Health-related quality of life in children with autism spectrum disorders: Results from the autism treatment network. *Journal of Autism and Developmental Disorders* 40: 721–729.

Licciardone JC, Smith-Barbaro P and Coleridge ST (2001) Use of the Internet as a resource for consumer health information: Results of the second osteopathic survey of health care in America (OSTEOSURV-II). *Journal of Medical Internet Research* 3(4): e31.

Lord C, Schopler E and Revicki D (1982) Sex differences in autism. *Journal of Autism and Developmental Disorders* 12: 317–330.

Lux V and Kendler KS (2010) Deconstructing major depression: a validation study of the DSM-IV symptomatic criteria. *Psychological Medicine* 40(10): 1679–1690.

Maenner MJ, Greenberg JS and Mailick MR (2015) Association between low IQ scores and early mortality in men and women: Evidence from a population-based cohort study. *American Journal on Intellectual and Developmental Disabilities* 120: 244–257.

Magiati I, Tay XW and Howlin P (2014) Cognitive, language, social and behavioural outcomes in adults with autism spectrum disorders: A systematic review of longitudinal follow-up studies in adulthood. *Clinical Psychology Review* 34: 73–86.

Meinshausen N and Bühlmann P (2006) High-dimensional graphs and variable selection with the lasso. *The Annals of Statistics* 34(3): 1436–1462.

Messinger D, Young GS, Ozonoff S, et al. (2013) Beyond autism: a baby siblings research consortium study of high-risk children at three years of age. *Journal of the American Academy of Child & Adolescent Psychiatry* 52: 300–308.

Miller I and Tuchman R (2011) Epileptic disorders. In: Howlin P, Charman T and Ghaziuddin M (eds) *The Sage Handbook of Developmental Disorders*. London: SAGE Publishing, pp.415–432.

Newman M (2010) *Networks: An Introduction*. New York: Oxford University Press.

Opsahl T, Agneessens F and Skvoretz J (2010) Node centrality in weighted networks: Generalizing degree and shortest paths. *Social Networks* 32: 245–251.

Paulhus DL, Lysy DC and Yik MS (1998) Self-report measures of intelligence: are they useful as proxy IQ tests? *Journal of Personality* 66(4): 525–554.

Petalas MA, Hastings RP, Nash S, et al. (2012) Psychological adjustment and sibling relationships in siblings of children with autism spectrum disorders: Environmental stressors and the broad autism phenotype. *Research in Autism Spectrum Disorders* 6: 546–555.

Pinquart M and Sörensen S (2000) Influences of socioeconomic status, social network, and competence on subjective well-being in later life: A meta-analysis. *Psychology and Aging* 15: 187–224.

Renty JO and Roeyers H (2006) Quality of life in high-functioning adults with autism spectrum disorder: The predictive value of disability and support characteristics. *Autism* 10: 511–524.

Robinaugh DJ, LeBlanc NJ, Vuletich HA, et al. (2014) Network analysis of persistent complex bereavement disorder in conjugally bereaved adults. *Journal of Abnormal Psychology* 123(3): 510–522.

Ruble LA and Dalrymple NJ (1996) An alternative view of outcome in autism. *Focus on Autism and Other Developmental Disabilities* 11: 3–14.

Ruggeri M, Bisoffi G, Fontecedro L, et al. (2001) Subjective and objective dimensions of quality of life in psychiatric patients: A factor analytical approach. *The British Journal of Psychiatry* 178: 268–275.

Sheldrick RC, Neger EN, Shipman D, et al. (2012) Quality of life of adolescents with autism spectrum disorders: Concordance among adolescents' self-reports, parents' reports, and parents' proxy reports. *Quality of Life Research* 21: 53–57.

Smith G (2008) Does gender influence online survey participation? A record-linkage analysis of university faculty online survey response behavior. Available at: http://www.eric.ed.gov/PDFS/ED501717.pdf (accessed 20 November 2015).

Stokes M, Newton N and Kaur A (2007) Stalking, and social and romantic functioning among adolescents and adults with autism spectrum disorder. *Journal of Autism and Developmental Disorders* 37: 1969–1986.

Tibshirani R (1996) Regression shrinkage and selection via the lasso. *Journal of the Royal Statistical Society: Series B—Methodological* 267–288.

Van Borkulo CD, Borsboom D, Epskamp S, et al. (2014) A new method for constructing networks from binary data. *Scientific Reports* 2, Article No. 5918.

Van Heijst BFC and Geurts HM (2015) Quality of life in autism across the lifespan: a meta-analysis. *Autism* 19: 158–167.

Volkmar FR, Szatmari P and Sparrow SS (1993) Sex differences in pervasive developmental disorders. *Journal of Autism and Developmental Disorders* 23: 579–591.

Walsh CE, Mulder E and Tudor ME (2013) Predictors of parent stress in a sample of children with ASD: pain, problem

behavior, and parental coping. *Research in Autism Spectrum Disorders* 7: 256–264.

White SW and Roberson-Nay R (2009) Anxiety, social deficits, and loneliness in youth with autism spectrum disorders. *Journal of Autism and Developmental Disorders* 39: 1006–1013.

Whitehouse AJ, Watt HJ, Line EA, et al. (2009) Adult psychosocial outcomes of children with specific language impairment, pragmatic language impairment and autism. *International Journal of Language & Communication Disorders* 44: 511–528.

Wigman JTW, Van Os J, Borsboom D, et al. (2015) Exploring the underlying structure of mental disorder: Cross-diagnostic differences and similarities from a network perspective using both a top-down and bottom-up approach. *Psychological Medicine* 45(11): 2375–2387.

Woodman AC, Smith LE, Greenberg JS, et al. (2016) Contextual factors predict patterns of change in functioning over 10 years among adolescents and adults with autism spectrum disorders. *Journal of Autism and Developmental Disorders* 46(1): 176–189.