Dynamic symptom networks across different at-risk stages for psychosis: An individual and transdiagnostic perspective

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ARTICLE INFO

Keywords:
Network analyses
Diary data
Clinical staging
Graphical vector autoregressive modeling (GVAR)
Intensive longitudinal data

ABSTRACT

The clinical staging model distinguishes different stages of mental illness. Early stages, are suggested to be more mild, diffuse and volatile in terms of expression of psychopathology than later stages. This study aimed to compare individual transdiagnostic symptom networks based on intensive longitudinal data between individuals in different early clinical stages for psychosis. It was hypothesized that with increasing clinical stage (i) density of symptom networks would increase and (ii) psychotic experiences would be more central in the symptom networks.

Data came from a 90-day diary study, resulting in 8640 observations within N = 96 individuals, divided over four subgroups representing different early clinical stages (n1 = 25, n2 = 27, n3 = 24, n4 = 20). Sparse Time Series Chain Graphical Models were used to create individual contemporaneous and temporal symptom networks based on 10 items concerning symptoms of depression, anxiety, psychosis, non-specific and vulnerability domains. Network density and symptom centrality (strength) were calculated individually and compared between and within the four subgroups.

Level of psychopathology increased with clinical stage. The symptom networks showed large between-individual variation, but neither network density nor psychotic symptom strength differed between the subgroups in the contemporaneous ($p_{density} = 0.59$, $p_{strength} > 0.51$) and temporal ($p_{density} = 0.75$, $p_{strength} > 0.35$) networks.

No support was found for our hypothesis that higher clinical stage comes with higher symptom network density or a more central role for psychotic symptoms. Based on the high inter-individual variability, our results highlight the importance of individualized assessment of symptom networks.

1. Introduction

Once established, psychotic disorders can have major impact on individual patients’ lives and society (Fusar-Poli et al., 2017; van Os and Kapur, 2009), with high levels of comorbidity and mortality (Oud and Meyboom-de, 2009). Therefore, early intervention, including good treatment selection and prognosis prediction, is of major importance (Iorfino et al., 2019). Clinical staging facilitates this by modeling the development of psychosis according to different, subsequent stages of illness severity (Iorfino et al., 2019; McGorry et al., 2006). These stages range from increased risk of psychotic or severe mood disorders without current symptoms (stage 0), to severe, chronic, or unremitting illness (stage 4). It is proposed that individuals in early stages, before a first episode of psychosis, have more transdiagnostic and fluid symptom expression, while in later stages, psychopathology becomes more persistent and domain-specific. Empirical investigation of the clinical staging model is still ongoing and it is yet unknown what drives progression through subsequent stages.

These hypothesized differences in symptom expression across stages can potentially be understood from a network perspective (Borsboom,
This approach conceptualizes psychopathology as a complex interplay between symptoms (Borsboom and Cramer, 2013), resulting in a network where symptoms represent ‘nodes’ (=observed variables) and connections between these nodes are represented by ‘edges’ (=statistical relationships) (Epskamp et al., 2018a, 2018b). The network theory proposes that individuals with (vulnerability for) psychopathology have highly connected symptom networks while resilient individuals have weakly connected networks (Borsboom, 2017). High connectivity between symptoms may lead symptoms, once activated by an external perturbation, to reactivate one another over time, leading to a stable state of more severe psychopathology (Borsboom, 2017; Klippen et al., 2018; Wichers et al., 2015; Wigman et al., 2015). Symptoms that have many and strong connections to other symptoms in a network are said to be ‘core-symptoms’ of this network, represented in high centrality. The dynamics between symptoms cannot be properly tested by means of cross-sectional data, as this neglects pathways of symptoms over time within individuals (Bak et al., 2016), or with group-level data, which neglects differences between individuals (Nelson et al., 2017). Intensive longitudinal data allows for modeling individual symptom interactions over time (Bringmann et al., 2013). Interactions between symptoms can occur within one time point (contemporaneous relationships) or over subsequent time points (temporal relationships) and ideally, both are assessed (Epskamp et al., 2018a, 2018b). Comparing individual symptom dynamics across individuals in different early clinical stages might offer valuable insights in how they differ and this, in turn, may lead to a better understanding of progression through subsequent clinical stages.

Another advantage of the network perspective is that it is well-equipped to accommodate a transdiagnostic approach, as it can be used to model associations between many variables at once. Several cross-sectional network studies have found that individuals with psychotic disorders have strong connectivity not only between psychotic symptoms (van Rooijen et al., 2017; van Rooijen et al., 2018), but also with symptoms of other psychopathological domains (Gelderis et al., 2014; Isvoranu et al., 2016). However, less is known about symptom dynamics in individuals with subclinical (not clinical) expressions of psychosis.

Addressing these issues, the aim of this study was to assess whether there are differences in symptom dynamics between and within four subgroups that represent different early clinical stages of psychosis. According to the staging model, higher stages are accompanied by an increasing risk for psychosis, which is the view that we adopt in this paper. We modeled individual contemporaneous and temporal symptom networks based on time-series data of daily assessments of ten transdiagnostic psychopathology and vulnerability items and derived from these networks symptom (i) network density and (ii) symptom centrality per individual. Note that, in line with other literature, we refer to these networks as ‘symptom networks’ but that the items represent daily experiences of psychopathological symptoms (e.g., ‘today I felt down’).

We expected to find differences in symptom dynamics between individuals in different clinical stages. First, we hypothesized that connections between items are stronger in individuals with a higher risk for psychosis, reflected in higher symptom network densities in higher clinical stages. Second, we expected a more domain-specific (“crystallized”) expression of psychopathology in higher clinical stages, represented in higher centrality of psychotic experiences in higher clinical stages.

2. Methods

2.1. Participants and study design

Data came from the Mapping Individual Routes of Risk and Resilience (Mirorr) study (N = 96). Mirorr is a daily diary study on psychopathology in young adults at risk for psychosis, with long-term follow-up assessments of mental health and functioning. The sample consists of four subgroups, each representing a different level of risk for psychosis, corresponding to early clinical stages 0-1b (Fig. 1). Subgroup 1 represents clinical stage 0 (increased risk), subgroup 2 early clinical stage 1a (mild non-specific symptoms), subgroup 3 late clinical stage 1a (mild more-specific symptoms), and subgroup 4 clinical stage 1b (at Ultra-High Risk (UHR) for psychosis). Subgroup 1 was sampled from the general population and did not receive mental health care; subgroups 2-4 were recruited from mental health care institutions and thus all received mental health care.

Inclusion criteria were: 1) aged between 18 and 35 years, 2) read and speak Dutch fluently, 3) capable of following the research procedures, and (4) informed consent. Exclusion criteria were: 1) history of or current psychotic episode according to the Diagnostic and Statistical manual of Mental Disorders 4 (DSM-4) criteria, 2) significant hearing or visual problem impairments, and 3) pregnancy.

This paper focused on data from the baseline measurement, which involved questionnaires and an interview about mental health and functioning and a daily diary study. The diary study required participants to complete a digital questionnaire once a day for 90 consecutive days. Participants were excluded from the study when they missed more than 22 measurements in total or missed five or more measurements in a row (n = 19). These diary data formed the basis for constructing individual symptom networks. For more details about participants, design and procedure, see Booij et al., 2018 and Wigman et al. (Under review).

2.2. Instruments

2.2.1. Demographic characterization

Subgroups were compared on age, gender, and education level (three categories: low (primary education or lower secondary education), medium (upper secondary education), and high (university/college education) (Central Bureau for Statistics, 2016).

2.2.2. Diary study

Diary items covered a broad transdiagnostic range of feelings and experiences that are typical for subclinical and clinical psychosis, depression, anxiety, mania, obsessive compulsive behavior and anger. For this study, ten items were selected based on item-content and within-person variability belonging to five domains of psychopathology and vulnerability: depression (feeling down and feeling empty), anxiety (feeling anxious and feeling worried), psychosis (feeling suspicious and feeling disliked), non-specific (feeling stressed and feeling irritated) and lack of confidence (not feeling confident, and not being able to handle what came my way) (Supplementary Table 1). The latter two items were positively framed in the diary study (“today I felt confident” and “I could handle what came my way today”) and were reverse coded. All items were scored on a 100-point VAS scale. These ten items were used as ‘nodes’ in the network.

2.2.3. Psychopathology

As indicator of general psychological distress, the total score of the Dutch Symptom Checklist Revised (Arrindell and Ettema, 2003) (SCL-90-R) was used. This self-report questionnaire consists of 90 questions on psychological symptoms during the past week scored on a 5-point scale, and has high reliability (Smits et al., 2015), with excellent internal consistency in our sample (Cronbach’s Alfa = 0.98).

The Community Assessment of Psychic Experiences (Konings et al., 2006) (CAPE) was used to describe level of subclinical psychotic experiences. The CAPE is a self-report questionnaire consisting of 42 questions concerning subclinical psychotic experiences. This questionnaire has good reliability and validity (Konings et al., 2006) and internal consistency in our sample (Cronbach’s Alfa = 0.89).

The Mini-SCAN was used to show the general psychiatric diagnoses in the four subgroups. The mini-SCAN is a valid (Nienhuis et al., 2010) and relatively short clinical interview that aims to assess psychiatric diagnoses (Nienhuis and Giel, 2000).
2.2.4. Social functioning

The Groningse Vragenlijst voor Sociaal Gedrag (GVSG) was used to measure social functioning (Jong and Lubbe, 2001). This self-report questionnaire covers nine social domains, whereof five concern interpersonal relationships (parents, partner, children below and above 15 years, and friends) and four social role functioning (education, paid/unpaid work, household chores, and leisure time). Each domain has five questions scored on a 4-point scale. The total score is based on the answers on the person-specific relevant domains (i.e. only subscales that apply to the person are taken into account). A higher score indicates better social functioning.

2.3. Statistical analysis

Missing data (9% per person on average, range 0–23%) was imputed per person by means of Linear moving average because it performed best after comparing six different imputation strategies (MICE, Amelia, mean imputation, Kalman smoothing, exponential moving average and linear moving average) in our dataset (Appendix A for more information). Second, a copula transformation was performed per individual per item to approach a normal distribution as close as possible (Nelsen, 1999).

2.3.1. Symptom networks

All analyses were performed in R version 3.6.1 (R Core Team, 2019). Symptom networks were estimated per individual (N = 96). Symptom networks can be contemporaneous, showing within-day associations of the variables at t (today), and temporal, showing between-day associations of the variables at t-1 (yesterday) and t (today). For the current study, both temporal and contemporaneous networks were estimated, as recommended by Epskamp et al. (2018a, 2018b). Symptom networks were created based on the coefficients produced by individual multivariate time series analysis by means of vector autoregressive (VAR) models (Brandt and Williams, 2007). VAR models regress a set of variables at a specific time point on themselves and all other variables in the model at previous time points (Brandimonte et al., 2013; Haslbeck and Waldorp, 2018). The specific VAR model used in this study is the Sparse Time Series Chain Graphical Model (TSCGM) (Abegaz and Wit, 2013). The TSCGM infers both contemporaneous and temporal partial correlations simultaneously. The partial correlations were used as edges in respectively the contemporaneous and temporal symptom networks. The TSCGM applies penalization that can deal with over-parametrized models (i.e. models with many parameters to be estimated as our model). The most commonly applied penalization is LASSO. However, this technique generates bias as the penalty term is linear to the size of the edge weight (i.e. a higher penalty applies to a large edge weight), meaning that coefficients are sometimes set to zero while they are actually true edges. Therefore, instead of LASSO, we used the Smoothly Clipped Absolute Deviation (SCAD) penalty (Fan and Li, 2001). SCAD is a compromise between unbiased maximum likelihood and the biased LASSO estimation and does not apply a penalty linear to the size of the edge weight. Thus, the size of the estimated coefficients is not shrunk as much as in LASSO and it is more likely that the true network structure is recovered. Tuning parameters control the penalization for edge weights in SCAD to help achieve sparsity in the network. Individual tuning parameters (Lambda) were selected according to the Akaike Information Criteria (AIC). With 90 time-points per individual, VAR analyses can reliably identify bi-directional associations between multiple variables (Rosmalen et al., 2012; van Gils et al., 2014).

The TSCGM assumes multivariate normality, lack of higher order autocorrelation for the residuals, and stationarity of the data. These assumptions were checked in several steps, described in detail in Appendix B.

After estimating the coefficients of the contemporaneous and temporal networks, the associations between the symptoms were visualized through the package qgraph (Epskamp, Cramer, Waldorp, Schmittmann, & Borsboom, 2012). Both symptom network visualizations were weighted, indicating that stronger edges were indicated with thicker lines. Temporal networks were directed, meaning that the direction of the association (from t-1 to t) was specified in the model.

Information from symptoms networks can be derived at the level of the total network and at the level of individual nodes. In this study, we investigated ‘network density’ as a characteristic of the total network and the symptom centrality measure ‘strength’ as a characteristic of individual nodes. Network density is the extent to which symptoms in the network are connected to each other and is defined as the ratio of the present number of edges to the total possible number of edges. Network density was calculated with the edge_density function of igraph (Csardi, 2006). The higher the network density, the stronger symptoms in the network are connected to each other. Symptom centrality indices can be used to quantify a node’s position in a network. Symptom strength is the most commonly used measure of symptom centrality (Brandimonte et al., 2019). Symptom strength was operationalized as the sum of the absolute value of all weighted edges of a node to all other nodes in the network (McNally, 2016). As edges in temporal networks are directed, a distinction was made between in-strength (=sum of all incoming edges) and out-strength (=sum of all outgoing edges) (Opsahl et al., 2010).
higher strength indicates that the symptom is more strongly connected to other symptoms in the network.

3. Results

3.1. Study sample characteristics

Table 1 summarizes demographical and clinical information per subgroup. The subgroups did not differ significantly on age and gender. General psychological distress, psychotic experiences and the mean number of diagnoses increased with increasing clinical stage, corroborating the model. The most often reported diagnosis on the mini-SCAN in all subgroups was ‘depression’.

Table 2 shows subgroup averages of untransformed within-person medians and Inter Quartile Ranges (IQR) for the diary items that were used to model individual symptom networks. Individuals in higher subgroups generally experienced more symptoms and showed more variability than individuals in lower subgroups.

3.2. Comparison of contemporaneous symptom networks between subgroups

One-way ANOVA showed that subgroups did not differ significantly on density (F(3, 92) = 0.64, p = .59). Kruskal-Wallis and ANOVA tests showed one significant difference on strength of the item ‘How stressed were you today’ (F(3,92) = 2.87, p = .041). Post-hoc comparison with TukeyHSD showed that individuals in subgroup 1 had significant lower strength than individuals in subgroup 2 (p = .049). No other differences in mean strength (p > .23) between the subgroups were found on any of the items (see Table 3 for the medians of strength).

In general, feeling down was relatively often in the top 2 of strength for all subgroups and psychotic items were less often in the top 2 (Supplementary Table 2). The vulnerability items are more often in the top 2 in the first three subgroups than in subgroup 4.

3.3. Comparison of temporal symptom networks between subgroups

One-way ANOVA showed that subgroups did not differ significantly on density (F(3, 92) = 0.41, p = .75). Kruskal-Wallis tests showed no significant differences in in-strength (p > .35) and out-strength (p > .37) between the subgroups in any of the items (Table 4).

Qualitative comparison of temporal symptom networks showed high variability within each subgroup with regard to which symptom had the highest in- and out-strength (Supplementary Table 3).

4. Discussion

4.1. Major findings

This study assessed potential differences in individual symptom networks between and within four subgroups representing different at-risk stages for psychosis (clinical stages 0-1b). Individuals in higher clinical stages showed higher levels of psychopathology in their daily diaries. In contrast to our hypotheses, the subgroups did not differ in symptom network connectivity nor in centrality of psychotic experiences. Several explanations for these findings are possible and depend on which perspective we take. Reasoning from the clinical staging model, our results do not support the network theory, as we did not find that individuals with an increased vulnerability for psychopathology have stronger network connectivity. Alternatively, reasoning from network theory, our findings could implicate that, even though the actual symptom levels increase with clinical stage, the dynamics that make one vulnerable for developing psychopathology, do not depend on (early) stages of illness.

4.1.1. Density

Our results did not show increased network density in subgroups at higher risk for psychosis, in contrast to previous empirical studies (Wigman et al., 2013; Klippel et al., 2018; Pe et al., 2014; van Borkulo et al., 2015; van Rooijen et al., 2018; Wigman et al., 2015; Wigman et al., 2017). There are several possible explanations for this incongruence. First, differences in network characteristics could only emerge in comparison with more severe illness stages. Most studies mentioned above focused on individuals with established illness (Pe et al., 2014; van Rooijen et al., 2018; van Borkulo et al., 2015; Wigman et al., 2015). Differences between the early, subclinical stages of psychosis represented in our study may have been too subtle to capture differences in symptom networks. Second, other previous network studies used either a cross-sectional design (van Borkulo et al., 2015; van Rooijen et al., 2018; Wigman et al., 2017), or an experience sampling method (ESM) approach with short measurement periods (often 5–7 days) and multiple measurements per day (often 8–10 times) (Wigman et al., 2013; Klippel et al., 2018; Pe et al., 2014; Wigman et al., 2015). Therefore, our results should be seen in light of our unique study design with daily assessments.

Table 1

| Demographics                          | Subgroup 1 | Subgroup 2 | Subgroup 3 | Subgroup 4 | Total group | Difference |
|---------------------------------------|------------|------------|------------|------------|-------------|------------|
| N                                     | 25         | 27         | 24         | 20         | 96          | ns         |
| Age mean (SD)                         | 23.3 (3.31) | 24.8 (3.88) | 26.1 (4.04) | 24.8 (5.15) | 24.7 (4.20) | ns         |
| Gender (% female)                     | 80.0       | 74.1       | 70.8       | 80.0       | 81.0        | ns         |
| Completed education                   |            |            |            |            |             |            |
| Low (%)                               | 4.0        | 18.5       | 8.3        | 30.0       | 14.5        | ns         |
| Middle (%)                            | 56.0       | 51.9       | 58.3       | 50.0       | 54.2        | ns         |
| High (%)                              | 40.0       | 25.9       | 29.2       | 20.0       | 29.2        | ns         |
| Other (%)                             | 0          | 4.0        | 4.0        | 0          | 2.1         |            |
| Clinical functioning                  |            |            |            |            |             |            |
| SCL-90 mean (SD)                      | 141.44 (38.24) | 174.78 (45.08) | 211.04 (56.09) | 232.50 (57.29) | 186.91 (59.34) | 4,3,2 > 1  |
| CAPE mean (SD)                        | 60.9 (9.61) | 67.5 (11.2) | 77.3 (15.3) | 75.4 (17.2) | 69.9 (14.72) | 4,3 > 1    |
| Positive symptoms                     | 23.5 (3.79) | 22.7 (2.23) | 26.3 (5.09) | 26.2 (5.26) | 24.6 (4.44) | 4,3 > 2    |
| Negative symptoms                     | 23.8 (5.14) | 28.0 (6.77) | 32.5 (7.77) | 31.0 (9.37) | 28.7 (7.91) | 4,3 > 1    |
| Depressive symptoms                   | 13.6 (3.29) | 16.9 (4.78) | 18.5 (5.39) | 17.7 (5.36) | 16.6 (5.03) | 4,3 > 1    |
| Mini-SCAN diagnoses Mean no. (SD)     | 0.36 (0.57) | 1.22 (0.85) | 2.04 (1.27) | 2.15 (1.27) | 1.40 (1.23) | 4,3 > 1    |

1 Significant difference p < .05, ns = not significant.

a Low = primary education or lower secondary education, Medium = upper secondary education, High = university/college education.
of a broad range of transdiagnostic symptoms for 90 days. Different approaches may capture different processes. Finally, it is possible that network connectivity is independent of the momentary level of psychopathology, as captured by the clinical staging model. Rather, high network connectivity poses a risk on individuals to develop more severe psychopathology in the future, not yet reflected in the present levels of psychopathology. A simulation study by Cramer et al. (2016) showed that individuals with highly connected networks have more chance at developing a depression than individuals with low connected networks, which aligns with the vulnerability hypothesis of the network theory (Borsboom, 2017).

Although contrasting with several studies, our findings are in line with others. Using cross-sectional data, Groen et al. (2019) did not find differences in individuals with different levels of psychopathological severity. Given the large differences in study design, samples, timeframes and measures used, direct comparison of all these studies is challenging and final conclusions on whether density changes with increasing psychopathology cannot be drawn yet.

### 4.2. Strengths and limitations

One important consideration is that we assessed daily experiences of psychopathological symptoms rather than symptoms in the strictest clinical sense. While these might not be 100% corresponding, it seems plausible to accept that they share a considerable overlap. This study is one of the first to adopt an individual, developmental and transdiagnostic approach to study symptom dynamics of individuals at risk for psychosis, and has notable strengths. First, several authors have argued that group-level associations cannot be generalized to the individual (Bos and De Jonge, 2014; Bos and Wanders, 2016; Fisher et al., 2018; Fried and Cramer, 2017; Hamaker, 2012) and the need to model symptom networks per individual rather than based on group data has been increasingly expressed (Fried et al., 2017; Klippel et al., 2018; van der Tuin et al., 2012; Stavrakakis et al., 2015).

### 4.1.2. Symptom strength

We did not find that psychotic experiences were more influential in networks of individuals in higher subgroups, despite higher levels of psychotic experiences. We did find that feeling stressed had a lower centrality in subgroup 1 than in subgroup 2. This might indicate that feeling stressed activates other symptoms in our specific network structure less in non-help seeking individuals than in help-seeking individuals with non-psychotic symptomatology.

Symptom strength of all symptoms was generally higher in same-day associations than in next-day associations. Currently, it is unknown what the best timeframe to measure psychopathological symptoms (Fried et al., 2017). Our results implicate that the dynamics between experiences used in our study might occur within the same day rather than over several days. It is important to realize that the contemporaneous relationships in our design do not represent exact same-moment associations but rather co-occurrence of symptoms within one day (Fisher et al., 2017; Greene et al., 2018), indicating that these symptoms might influence each other over a shorter timeframe than 24 h.

Symptom centrality has been proposed as an important target for treatment since highly central symptoms affect many other symptoms (Fried et al., 2017). Our results indicated that the best symptoms to be targeted should be derived from individual networks rather than group level networks, because centrality indices and their direction of influence might be very different for different individuals (Fisher et al., 2017; Rosmalen et al., 2012; Stavrakakis et al., 2015).
out-strength.

parametric tests. Third, there was a trade-off between comparability of measurements per person rather than just one measurement as in cross-sectional research, which increased measurement precision and hence power. Second, because subgroups were based on 90 measurements per person rather than just one individual's data, we performed non-parametric tests, which are less sensitive than normal distribution and forcing variances to be similar to circumvent this problem. In addition, we checked and our results were not driven by general psychopathology or social functioning (Appendix C). Finally, a general criticism on the symptom network approach concerns the replicability and stability of the networks (Fried and Cramer, 2017). Stability tests are available for cross-sectional symptom networks of groups; however, to date, there are no tests for time-lagged individual analyses, and thus we were not able to test the stability of our symptom networks.

4.3. Directions for future research

Future studies should focus on unraveling further whether the risk of developing psychopathology is better captured by current severity of symptoms, as in the clinical staging model, or by symptom dynamics, as in the network theory. This can only be answered by longitudinal studies that assess both symptom dynamics and symptom severity. The heterogeneity of our sample should be further investigated, for example with (Confirmatory) Subgrouping Group Iterative Multiple Model Estimation (CS-GIMME), which allows for modeling networks at group-, subgroup- and individual-level models simultaneously. Finally, our results should be replicated with different designs, as the outcome of analyses using diary data is still highly dependent on choices made by researchers (Bastiaansen et al., 2020).

Funding

This work was supported by a grant from the Netherlands Organization for Scientific Research (NWO) (Veni grant: no. 016.156.019) to JTWW.

Declaration of competing interest

None.

Acknowledgements

We would like to thank all research assistants, and in particular Merel Karlijn Muller, for their valuable contribution to the data collection. We also would like to thank all Mirror participants for their contributions. Finally, we would like to thank dr. Laura Bringmann for her statistical advice on node centrality.

Appendices. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.schres.2021.11.018.

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Rooijen et al., 2017; van Rooijen et al., 2018; Wigman et al., 2017). Our study is one of the first to do this. Second, due to the longitudinal design, dynamics of symptoms over a long period of 90 days could be assessed. Third, the transdiagnostic approach allowed for assessing a wide variety of symptoms which might better approximate clinical reality, especially in early clinical stages, than a sole focus on only psychotic experiences (Fried and Cramer, 2017; Hartmann et al., 2019; McGorry et al., 2018).

This study also had limitations. The relatively small number of individuals in each subgroup decreased the power to detect differences between clinical stages. However, the individually calculated centrality indices were based on 90 measurements per person rather than just one measurement as in cross-sectional research, which increased measurement precision and hence power. Second, because subgroups were relatively small and the centrality indices not always normally distributed, we performed non-parametric tests, which are less sensitive than parametric tests. Third, there was a trade-off between comparability of symptom networks and improving individual assumptions and fit in the analyses. We generally favored the first over the latter option, implying that some of the individual models had a suboptimal fit. Terluin et al. (2016) criticized the study by Wigman et al. (2013), where they found differences in network density between subgroups with increasing levels of psychopathology, arguing that their results may also be explained by differences in severity and variance (Terluin et al., 2016). In our study, we performed a copula transformation per individual to achieve a normal distribution and forcing variances to be similar to circumvent this problem. In addition, we checked and our results were not driven by general psychopathology or social functioning (Appendix C). Finally, a general criticism on the symptom network approach concerns the replicability and stability of the networks (Fried and Cramer, 2017). Stability tests are available for cross-sectional symptom networks of groups; however, to date, there are no tests for time-lagged individual analyses, and thus we were not able to test the stability of our symptom networks.

Table 4

| Subgroup | Subgroup | Subgroup | Subgroup | Total |
|----------|----------|----------|----------|-------|
|          | 1        | 2        | 3        | 4     | group |
| Mean (SD)|          |          |          |       |       |
| Network density |           |           |           |       |       |
| 0.36 (0.17) | 0.32 (0.18) | 0.35 (0.18) | 0.38 (0.18) | 0.35 (0.17) |

In-strength

| Measure | Mean (SD) |       |       |       |       |
|---------|-----------|-------|-------|-------|-------|
| Down    | 0.30 (0.36) | 0.24 (0.39) | 0.38 (0.48) | 0.33 (0.47) | 0.33 (0.40) |
| Empty   | 0.28 (0.50) | 0.19 (0.43) | 0.20 (0.57) | 0.23 (0.59) | 0.22 (0.53) |
| Anxious | 0.24 (0.47) | 0.33 (0.31) | 0.23 (0.63) | 0.34 (0.59) | 0.25 (0.51) |
| Worried | 0.27 (0.30) | 0.31 (0.37) | 0.24 (0.54) | 0.35 (0.39) | 0.29 (0.47) |
| Suspicious | 0.23 (0.39) | 0.09 (0.29) | 0.21 (0.44) | 0.33 (0.44) | 0.21 (0.45) |
| Disliked | 0.31 (0.36) | 0.15 (0.50) | 0.22 (0.40) | 0.33 (0.54) | 0.24 (0.46) |
| Stressed | 0.32 (0.47) | 0.26 (0.37) | 0.22 (0.48) | 0.48 (0.39) | 0.27 (0.44) |
| Irritated | 0.19 (0.41) | 0.18 (0.49) | 0.30 (0.51) | 0.35 (0.44) | 0.29 (0.51) |
| Not confident | 0.22 (0.29) | 0.23 (0.49) | 0.32 (0.27) | 0.33 (0.51) | 0.28 (0.57) |
| Not handle | 0.20 (0.48) | 0.30 (0.37) | 0.33 (0.54) | 0.34 (0.28) | 0.31 (0.39) |

Out-strength

| Measure | Mean (SD) |       |       |       |       |
|---------|-----------|-------|-------|-------|-------|
| Down    | 0.33 (0.35) | 0.14 (0.50) | 0.26 (0.50) | 0.26 (0.55) | 0.25 (0.49) |
| Empty   | 0.23 (0.39) | 0.26 (0.45) | 0.14 (0.29) | 0.32 (0.64) | 0.26 (0.47) |
| Anxious | 0.28 (0.31) | 0.29 (0.46) | 0.24 (0.50) | 0.33 (0.16) | 0.29 (0.34) |
| Worried | 0.26 (0.27) | 0.22 (0.35) | 0.26 (0.49) | 0.24 (0.39) | 0.25 (0.36) |
| Suspicious | 0.32 (0.50) | 0.30 (0.31) | 0.18 (0.31) | 0.28 (0.44) | 0.29 (0.33) |
| Disliked | 0.29 (0.50) | 0.19 (0.34) | 0.30 (0.26) | 0.31 (0.25) | 0.29 (0.55) |
| Stressed | 0.33 (0.48) | 0.19 (0.34) | 0.38 (0.26) | 0.38 (0.25) | 0.33 (0.55) |
| Irritated | 0.32 (0.48) | 0.24 (0.27) | 0.22 (0.25) | 0.34 (0.51) | 0.28 (0.40) |
| Not confident | 0.34 (0.34) | 0.18 (0.37) | 0.32 (0.61) | 0.27 (0.38) | 0.27 (0.42) |
| Not handle | 0.27 (0.29) | 0.22 (0.52) | 0.22 (0.51) | 0.53 (0.47) | 0.23 (0.38) |
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