Rubicon:
Grant application form 2017

(deadline 29 March 2018, 14.00 hrs. (2 PM) CE(S)T)

2. Research proposal

2a. Proposed research

Subject and aim of the research

The aim of this project is to combine three lines of research in network psychometrics: (1) generalized network psychometrics (GNP; [**27**]), allowing for combining network models with latent variable models, (2) multi-level network estimation, allowing for separating intra-individual and inter-individual network structures, and (3) bootstrap stability measures, allowing to assess the accuracy and stability of results. The project will combine these lines of research in two ways: (I) multi-level GNP for intra-individual models, and (II) accuracy standards for interpreting GNP results.

Current state of knowledge in the field

The *network perspective* on psychology conceptualizes observed variables (e.g., attitudes, symptoms, and moods) as causal agents in a complex interplay of psychological, biological, sociological and other components [4,**5**,14]. The field of *network psychometrics* aims to estimate network models from psychological datasets in an attempt to map out this complex interplay [**26**]. These network models visualize observed variables as nodes and the strength of conditional association between two variables after controlling for all other variables as links [**22**]. Network models are powerful tools to discover psychological dynamics, map out multicollinearity and predictive effects [**29**], approximate the joint likelihood of observed variables [**26**,47], and to extend latent variable modeling [**27**,**37**,52]. Several software packages have been developed to facilitate research in estimating these models, assessing their accuracy and visualizing the results [**23**,**22**,**18**,**19**,**24**,39,**60**]. Network Psychometrics is utilized in different research fields [36], such as depression [9,**35**,56], post-traumatic stress [1,33,48,49], schizophrenia [2,41,40,51,59], comorbidity [3,7,53], autism [17,54], personality [**11**,12,13], attitude formation [15,16], intelligence research [42,57,58], health sciences [**43**,**45**], and clinical practice [**28**,30,44].

When data are continuous, the most commonly used network model is the *Gaussian graphical model* [**25**,46], a network of partial correlation coefficients (Figure 1). For a set of variables, $\boldsymbol{y}$, that are assumed normally distributed with mean vector $\boldsymbol{\mu}$ and variance-covariance matrix $\boldsymbol{\Sigma}$:

$$y \sim N(\boldsymbol{\mu}, \boldsymbol{\Sigma})$$

the GGM can be modelled using the following psychometric model [**27**]:

$$\boldsymbol{\Sigma} = \boldsymbol{\Delta}(\mathbf{I} - \boldsymbol{\Omega})^{-1}\boldsymbol{\Delta},$$

in which $\boldsymbol{\Delta}$ is a diagonal scaling matrix, and $\boldsymbol{\Omega}$ is a square and symmetrical model-matrix including zeroes on the off-diagonal and partial correlation coefficients (encoding the network structure) on the off-diagonal elements. Degrees of freedom can be obtained by constraining elements of $\boldsymbol{\Omega}$ to zero; model-search algorithms or regularization techniques can be used to exploratively determine which elements of $\boldsymbol{\Omega}$ can be set to zero. Of note, the expression above is identical to inverting $\boldsymbol{\Sigma}$, standardizing the result, and multiplying all off-diagonal elements by -1 [**29**].

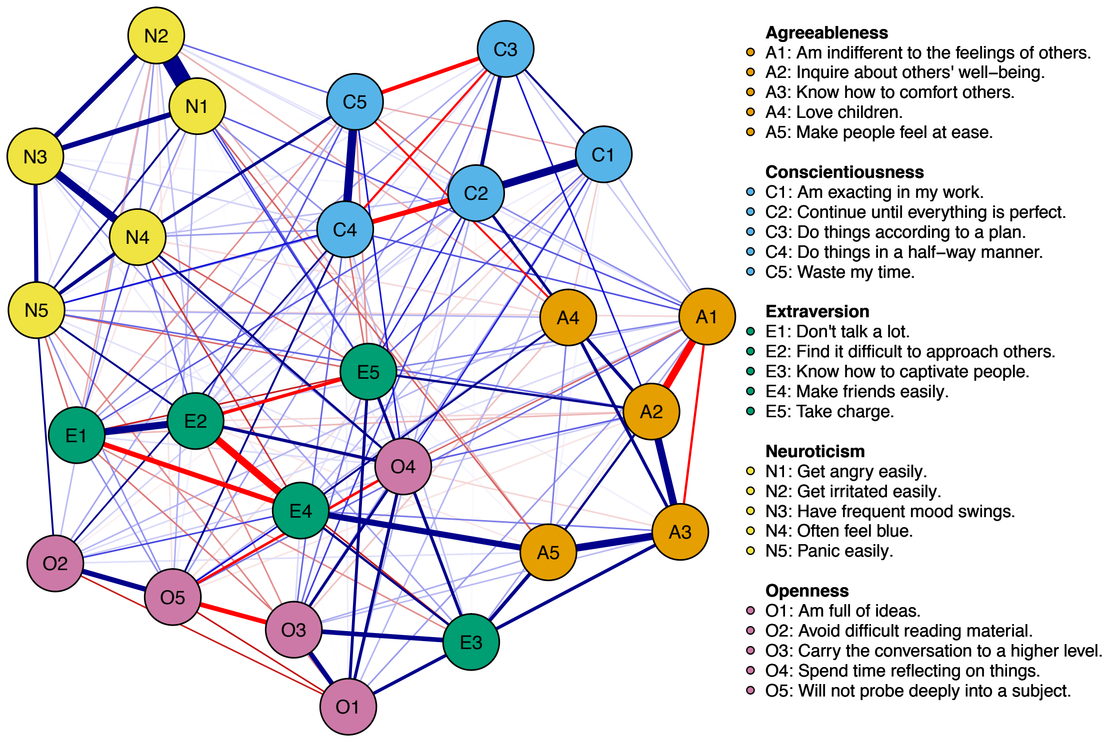


Figure 1. Estimated Gaussian graphical model ([**20**], chapter 1). Blue (red) links indicate positive (negative) partial correlations.

Several researchers have criticized the estimation of GGM models (and related network models) from data:

1. Network models rely on the assumption that all causally interacting variables are observed without error. In psychological data, however, we may always assume a certain level of measurement error [31,55]. Network models currently cannot deal with this measurement error.
2. While network modeling has been proposed as an alternative to latent variable modeling (i.e., covariation is caused by one or more unobserved common causes), it has been suggested that the complete omission of latent variables may be one step too far [8,34,38]; it is well plausible that some unobserved common causes underlie the data even though a network structure also explains covariation.
3. Network models are now often estimated from cross-sectional data. However, it has been suggested that such results are not reflective of within-person dynamics over time [6,50].
4. Network models, and especially derived descriptives such as centrality measures, may be unstable and poorly replicable in new samples [**21**,32,33].

In prior work, I have proposed solutions to all above-mentioned problems. The aim of this project is to bring these solutions together.

Solution 1: Generalized network psychometrics. Problems 1 and 2 can be overcome by combining network models with latent variable models (Figure 2). Suppose the observed variables $\boldsymbol{y}$ are reflective of a set unobserved causes $\boldsymbol{\eta}$ (not including subject subscripts for notational clarity):

$$\boldsymbol{y} = \boldsymbol{\Lambda\eta} + \boldsymbol{\varepsilon};\ \boldsymbol{\eta} \sim N(\boldsymbol{0}, \boldsymbol{\Psi});\ \boldsymbol{\varepsilon} \sim N(\boldsymbol{0}, \boldsymbol{\Theta}),$$

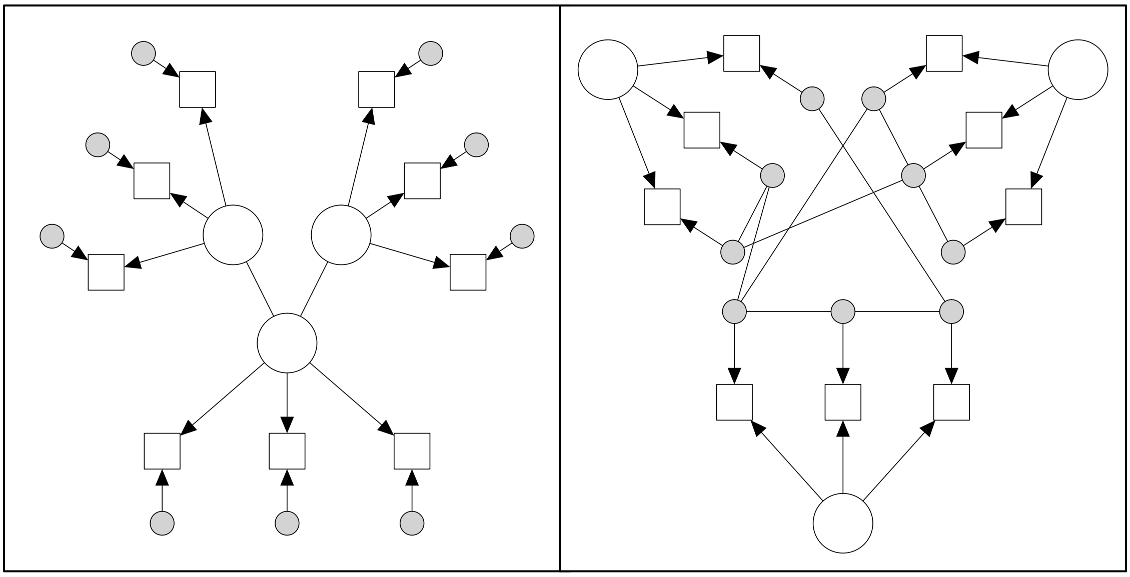
in which $\boldsymbol{\Lambda}$ denotes a factor-loadings matrix, $\boldsymbol{\Psi}$ a (typically fully populated) variance—covariance matrix of latent variables that may be further modeled using structural effects (structural equation modeling; SEM) and $\boldsymbol{\Theta}$ a (typically diagonal) variance—covariance matrix of residuals. This expression is well known as a factor model. The GNP framework [**27**] suggests this framework can be extended in two ways. First, by modeling $\boldsymbol{\Psi}$ as a GGM:

$$\boldsymbol{\Psi} = \boldsymbol{\Delta}_{\boldsymbol{\Psi}}(\mathbf{I} - \boldsymbol{\Omega}_{\boldsymbol{\Psi}})^{-1}\boldsymbol{\Delta}_{\boldsymbol{\Psi}},$$

also termed latent network modeling (LNM). Second, by modeling $\boldsymbol{\Theta}$ as a GGM:

$$\boldsymbol{\Theta} = \boldsymbol{\Delta}_{\boldsymbol{\Theta}}(\mathbf{I} - \boldsymbol{\Omega}_{\boldsymbol{\Theta}})^{-1}\boldsymbol{\Delta}_{\boldsymbol{\Theta}},$$

also termed residual network modeling (RNM). The LNM framework offers a solution to problem 1 (measurement error), by modeling a network structure between latent variables. The RNM framework offers a solution to problem 2 (no latent variables), by allowing the inclusion of common causes and exploratory estimation of a sparse (many elements equal to zero) residual network $\boldsymbol{\Omega}_{\boldsymbol{\Theta}}$. Of note, both frameworks also solve problems in latent variable modeling: LNM allows for explorative structure estimation between latent variables, and RNM allows for the estimation of latent variable models where local independence is structurally violated (a sparse $\boldsymbol{\Omega}_{\boldsymbol{\Theta}}$ may lead to a fully populated $\boldsymbol{\Theta}$ leading to all residuals to be correlated). Furthermore, GNP allows for confirmatory modeling of GGMs by not including a latent variable structure in the RNM.



(a) Latent network model (b) Residual network model

Figure 2. Examples of generalized network psychometrics (GNP) models.

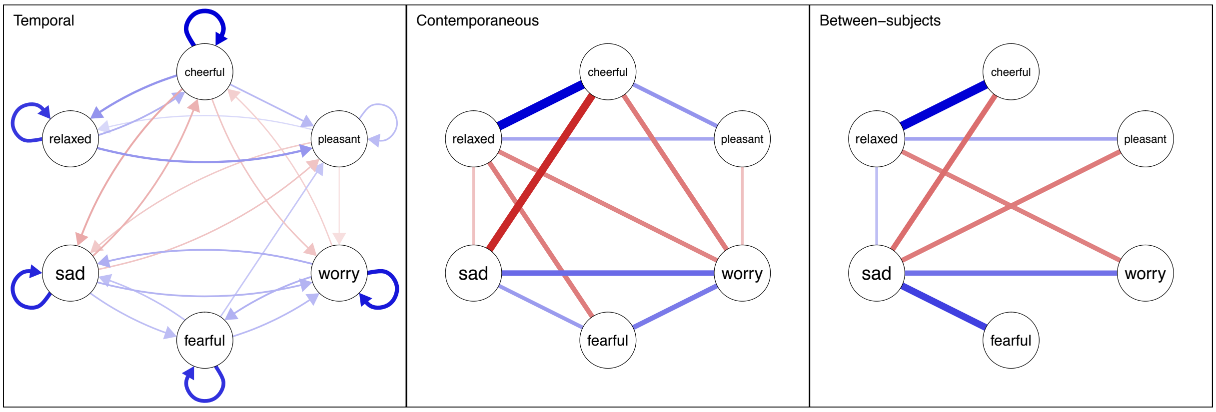


Figure 3. Estimated network structures from time-series data of multiple subjects [**29**].

Solution 2: Multi-level network modeling. To study general within-person dynamics in the population, a possible course of action is to gather time-series data of multiple subjects. The vector-autoregression (VAR) framework is now routinely applied to capture within-person dynamics over time in temporal network. Multi-level routines allow for estimating such models in multiple subjects, in order to gain insight in average effects in the population as well as individual differences in the network structures [10]. Recently, multi-level VAR estimation has been generalized to include GGMs at the contemporaneous and between-subject levels ([**29**]; figure 2).

Solution 3: Bootstrapped stability and accuracy checks. Bootstrapping methods have been proposed, and are now commonly used, to assess the stability and accuracy of network structures [**21**], and derived descriptive statistics such as centrality indices quantifying the importance of nodes. While the GNP framework allows for confirmatory fit-indices of network models, these are typically good in explorative network studies and may not reflect instability of results. It has been shown that typical non-parametric bootstrap routines are not suitable for centrality indices [**21**]. To this end, the correlation-stability coefficient has been suggested as a measure for assessing the stability of indices while dropping cases from the analysis.

Advancements in current state of knowledge

While solutions to problems in network modelling have been proposed separately, the aim of this proposal is to bring these solutions together. This will advance the current state of knowledge in two separate projects: (I) developing multi-level GNP models, and (II) implementing bootstrapping methods for GNP models and deriving accuracy and stability standards using simulation studies.

Project I1: Multi-level GNP Models. The first project will combine GNP models with *multi-level SEM* to obtain multi-level GNP models. This will allow researchers to disentangle within- and between-subject variance in GNP models. Furthermore, multi-level modelling allows one to estimate individual models per person, while borrowing information from other persons [**29**]. Extending GNP to multi-level modelling can be seen as a natural generalization of multi-level SEM in which not marginal (residual or latent) covariances are modelled, but rather partial covariances are modelled. In this project, large-scale simulation studies will be performed to assess the performance of multi-level GNP and to provide guidelines for empirical researchers in terms of sample size and number of variables needed to perform such an analysis.

Project II: Stability and accuracy standards for GNP models. The second project will focus on determining stability and accuracy standards for GNP models (both regular and multi-level). The advancements of this project will mostly be practical: current software for estimating GNP models is slow and does not lend itself easily for bootstrapping methods. In addition, feasibility standards, such as the suggested correlation-stability coefficient levels for regular network models [**21**], need to be determined for the stability and accuracy of GNP models. In this project, software to estimate GNP models will be improved to estimate GNP models faster, and bootstrapping routines will be implemented to assess the accuracy and stability of GNP models. Large-scale simulation studies will be used to determine standards for interpreting results from GNP models to be stable.

Innovative aspect of research proposal

This Rubicon project proposes innovative applications of an already novel modelling framework. Both the multi-level extensions as well as the bootstrapping methods for assessing stability will prove valuable in further fleshing out GNP methodology and making this promising framework readily useable to answer questions researchers are interested in.

Research method(s) to be used

The proposed projects are methodological studies to extend a methodological framework. To this end, the projects will mainly use technical derivations to derive the mathematical background of the proposed modelling framework, programming to implement the proposed methods in accessible software packages, and simulation studies to assess the performance of proposed methods in practice.

Means of publication/dissemination of research results

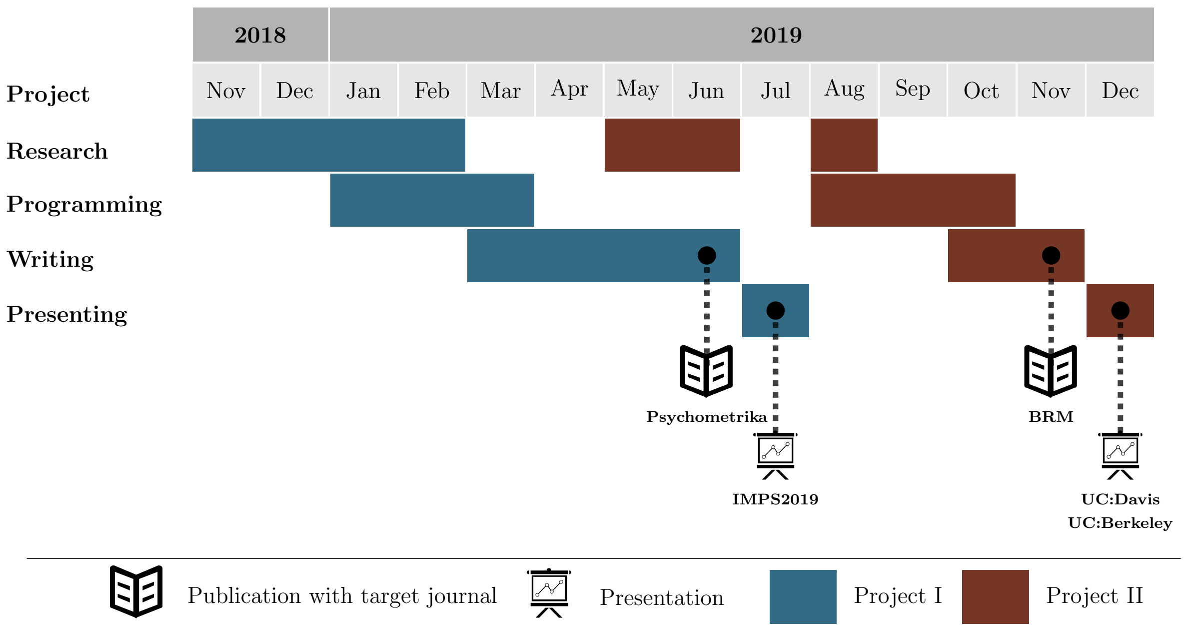
<u>Project I will result in a technical paper aimed at psychometricians and methodologists and project II will result in a non-technical paper aimed at empirical researchers:</u>

I. A paper describing multi-level GNP models and how these can be estimated.
II. A paper describing simulation studies to provide guidelines for the accuracy and stability of GNP models using bootstrapping methods.

The applicant has been awarded the prestigious Psychometric Society dissertation prize 2018, which includes an invitation to submit an article to the flagship journal in psychometrics: *Psychometrika*. The deadline for this invitation is July 31, 2019, and the subject of the invited article is the dissertation of the applicant. This invited article is naturally suited for the results from Project I, and will form the target publication for its results. Project II is aimed to be submitted to the well-known methodological journal *Behavorial research methods* by December 2019.

In addition to the two papers, results will also be implemented in updates to existing R packages: the *lvnet* package for GNP models [**19**], and the *bootnet* package for bootstrapping methods [**24**]. Finally, results will be presented at the International Meeting of the Psychometric Society (IMPS) in 2018 as well as through presentations at the University of California, Berkeley (UC:Berkeley) and University of California, Davis (UC:Davis).

Plan of activities (including research timetable and phasing)



2b. Literature references

List all relevant literature here and include full bibliographical details, e.g. Authors, *Title article,* Title book/journal, ed., year, page nrs.

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2c. Ethical aspects

Possible relevant aspects are:
- research on animals
- informed consent
- privacy and data protection