SYMPOSIUM

Latest scientific developments in the implementation of personalized feedback in psychiatric care

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Personalized Networks in Clinical Practices: Recent developments, Challenges and Future Directions.

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The Network Perspective

Mapping out Psychological Complexity

Two ways in which psychological networks can be obtained:

• **Estimation**
  - Agnostic network estimation has been worked out
  - Useful for hypothesis generating exploratory insight
  - *Network Psychometrics*

• **Theory**
  - Conceptual: Clinical expertise and patient experiences can be used to form a conceptual clinical theory per patient
  - Formal: Such theories could further be formalized using mathematical modeling (e.g., dynamical systems modeling)
To estimate a personalized (network) model, personal data is required!

Time-series analysis of patients in clinical practice
Temporal effects

- The temporal network shows that one variable predicts another variable in the *next* measurement occasion.
- *Granger causality*
### Contemporaneous effects

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<th>nervous</th>
<th>concentration</th>
<th>tired</th>
<th>rumination</th>
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- The contemporaneous network shows that two variables predict one-another after taking temporal information into account.
- Contains effects faster than the time-window of measurement.
  - Somatic arousal $\rightarrow$ anticipation of panic attack $\rightarrow$ anxiety.
Personalized Networks in Clinical Practice

(a) Temporal network – Patient 1

(b) Contemporaneous network – Patient 1

Graphical Vector Auto-regression

- Contemporaneous network: conditional concentration given $t - 1$
- Temporal network: regression coefficients between $t - 1$ and $t$
Estimating Networks in Clinical Practice

- Estimating network models in clinical practice is an *addition* to the clinical toolbox, not a replacement!
- Can be used for hypothesis generating insight by the clinician
- Not the full story: looking at the descriptives is also useful!
Riese, H., Servaas, M. N., Epskamp, S., & van der Veen, D. C.


Challenges to Personalized Network Modeling

- Lag interval and model complexity
  - Lag interval is very important for interpretation of temporal networks

- Practical limits in clinical practice:
  - Patients cannot fill in questionnaires many times per day or (typically) over a period of several months
  - Models need to be kept simple in response (e.g., lag-1)

- Required number of observations and feasibility
  - As networks are a complicated combination of many parameters, power analysis is not trivial. More simulation studies needed!

- Incorporating prior knowledge
  - Clinical expertise and patient experience should be able to help model estimation

- Intervention selection
  - Automatic selection of intervention strategy still complicated
  - Theoretical models needed on which interventions can be simulated
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Personalized Network Modeling in Psychopathology: The Importance of Contemporaneous and Temporal Connections

Sacha Epskamp, Claudia D. van Borkulo, Date C. van der Veen

Abstract

Recent literature has introduced (a) the network perspective to psychology and (b) collection of time series data to capture symptom fluctuations and other time varying factors in daily life. Combining these trends allows for the estimation of intraindividual network structures. We argue that these networks can be directly applied in clinical research and practice as hypothesis generating structures. Two networks can be computed: a temporal network, in which one investigates if symptoms (or other relevant variables) predict one another over time, and a contemporaneous network, in which one investigates if symptoms predict one another in the same window of measurement. The contemporaneous network is a partial correlation network, which is emerging in the analysis of cross-sectional data but is not yet utilized in the analysis of time series data. We explain the importance of partial correlation networks and exemplify the network structures on time series data of a psychiatric patient.
Model: Emotion-Regulation via Avoidance/Substance Use

• **Negative Thoughts (IV)** lead to avoidance strategies, e.g. **Substance Use (S)**, in turn decreasing **Negative Thoughts**.

• **Substance Use (S)** on the other hand leads to an increase in **Stressors (Ba)**, e.g. problems at work or social contexts, subsequently increasing **Negative Thoughts (IV)**.

• On the other hand, **Substance Use (S)** leads to the development of **Tolerance (I)** towards the effects of the substance, moderating the effects of the substance on **Negative Thoughts (IV)**.

Work in progress by Julian Burger
Theory can be translated to a formal mathematical model:

\[
\frac{dIV}{dt} = IV \times (1 - IV) \times (F_p - G - S \times (B - E \times I))
\]

\[
\frac{dS}{dt} = A \times IV \times (1 - S) - H \times S
\]

\[
\frac{dI}{dt} = C \times S \times (1 - I) - D \times I
\]

\[
\frac{dBa}{dt} = J \times S \times (1 - Ba) - K \times Ba
\]

Work in progress by Julian Burger
Differential Equations and Equilibrium

Stressor → Neg. Thoughts (IV) → Tolerance (I) → Avoidance (S)

IV

S

I

Ba

Work in progress by Julian Burger
Incorporating random Mood Swings and Stressors

random Mood Swings

random Stress
Events in Everyday life

Work in progress by Julian Burger
Behavioral Therapy: Reducing Substance Use from $t = 4000$

Intervention 1: Reduce Substance Use at $t = 4000$

Work in progress by Julian Burger
Cognitive Therapy: Providing Tools to regulate Negative Thoughts from $t = 4000$

Intervention 2: Cognitive Therapy from $t = 4000$

Work in progress by Julian Burger
Combined Approach (Cognitive Behavioral Therapy): Providing tools to regulate Negative Thoughts and reduce Substance Use from $t = 40000$

Work in progress by Julian Burger
Thank you for your attention!

- Website: sachaepskamp.com
  - Slides at: sachaepskamp.com/presentations
- Twitter: twitter.com/SachaEpskamp
- Join our Facebook group!
  - facebook.com/groups/PsychologicalDynamics
- Special thanks to Julian Burger, Harriette Riese, Date van der Veen, Michelle Servaas, Rick Quax and Donald Robinaugh
Extra: Systems dynamic model for diabetes

Work in progress by Jonathan Jeroen Beekman, Karien Stronks, Mary Nicolaou, Rick Quax, and Peter Sloot.