Title: Dynamic Longitudinal Modeling

Instructors: Manuel Voelkle & Charles Driver

Abstract:

The goal of this workshop is to introduce participants to advanced modeling techniques, focusing on dynamic approaches to analyzing change and variability. We will begin by differentiating static and dynamic models, discussing their respective strengths and weaknesses, and exploring the fundamentals of dynamic modeling, including practical tools and software.

Throughout the workshop, we will cover key topics such as addressing heterogeneity, applying hierarchical models, analyzing individual-level data, and exploring innovative study designs. Participants will also be introduced to cutting-edge methods for causal inference and the integration of machine learning into dynamic modeling, with an emphasis on their practical applications and current limitations.

While examples will primarily draw from applied research, the workshop is designed for participants with an interest in quantitative methods. Prior experience with multivariate analysis is beneficial but not required, and familiarity with structural equation modeling and longitudinal data analysis is helpful. Emphasis will be placed on practical implementation using datasets and software tools.

Prerequisites:

Participants should bring their own laptops with the latest versions of R and RStudio installed. Those new to R are encouraged to familiarize themselves with its basic functionality. Advanced knowledge of R is not necessary for participation.

Assignment: Active participation

Credits: 4 workshop days

<u>Literature:</u>

We do not expect that you prepare any readings in advance. Specific readings will be provided in class. Much of the workshop will be based on the following literature.

- Driver, C. C., Oud, J. H. L., & Voelkle, M. C. (2017). Continuous Time Structural Equation Driver, C. C. (2024). Inference with cross-lagged effects—Problems in time. Psychological Methods. https://doi.org/10.1037/met0000665
- Driver, C. C., & Tomasik, M. J. (2023). Formalizing developmental phenomena as continuous-time systems: Relations between mathematics and language development. *Child* Development, 94(6), 1454–1471. https://doi.org/10.1111/cdev.13990
- Driver, C. C., Oud, J. H. L., & Voelkle, M. C. (2017). Continuous Time Structural Equation Modeling with R Package ctsem. *Journal of Statistical Software*, 77(5), 1–35. doi.org/10.18637/jss.v077.i05
- Driver, C. C., & Voelkle, M. C. (2018). Hierarchical Bayesian continuous time dynamic modeling. Psychological Methods, 23(4), 774–799. dx.doi.org/10.1037/met0000168
- Orzek, J. H., & Voelkle, M. C. (2023). Regularized continuous time structural equation models: A network perspective. Psychological Methods, 28(6), 1286-1320. https://doi.org/10.1037/met0000550
- Van Montfort, K., Oud, J. H., & Voelkle, M. C. (Eds.). (2018). Continuous time modeling in the behavioral and related sciences. Springer International Publishing.
- Voelkle, M. C., Gische, C., Driver, C. C., & Lindenberger, U. (2018). The role of time in the quest for understanding psychological mechanisms. *Multivariate Behavioral Research*, 53(6), 782–805. doi.org/10.1080/00273171.2018.1496813
- Voelkle, M. C., Oud, J. H., Davidov, E., & Schmidt, P. (2012). An SEM approach to continuous time modeling of panel data: relating authoritarianism and anomia. *Psychological Methods*, 17(2), 176–192. doi.org/10.1037/a0027543
- Voelkle, M. C., & Oud, J. H. (2013). Continuous time modelling with individually varying time intervals for oscillating and non-oscillating processes. British Journal of Mathematical and Statistical Psychology, 66(1), 103–126. doi.org/10.1111/j.2044-8317.2012.02043.x