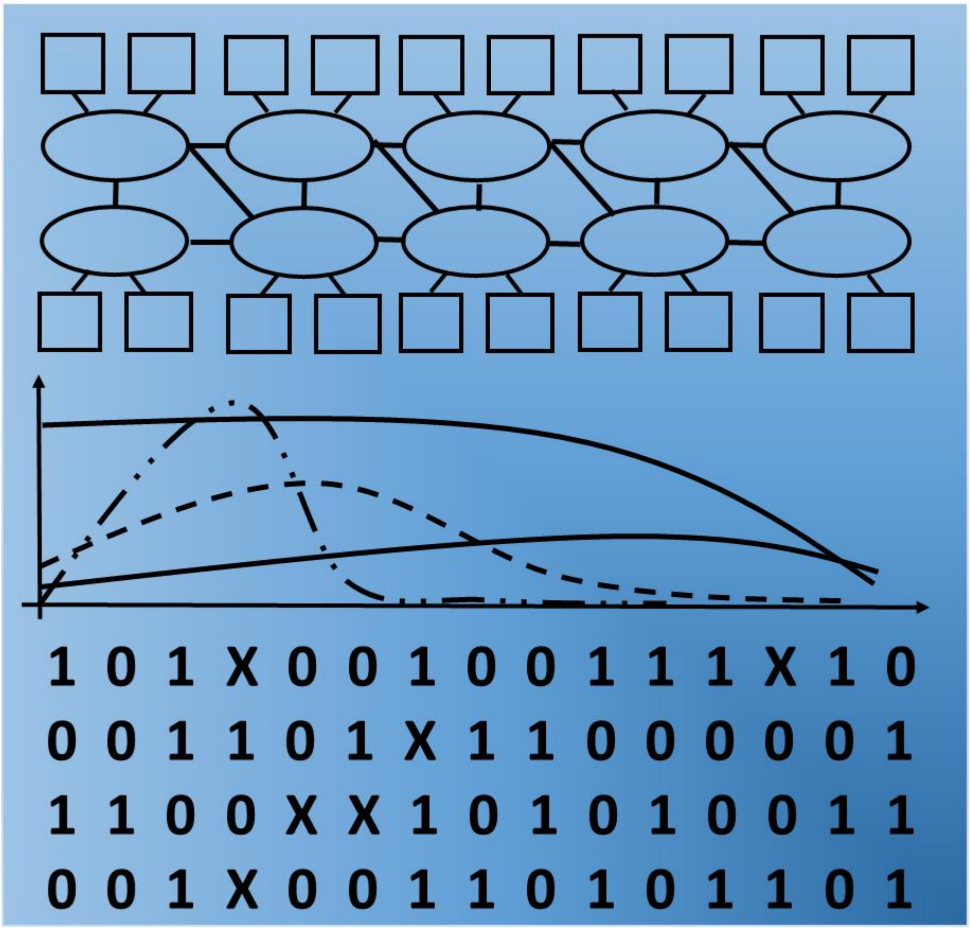
**Advanced Techniques for Longitudinal Data Analysis in Social Science**

**(ATLASS2023)**

# BOOK OF ABSTRACTS




March 14 to 17, 2023, Bielefeld, Germany

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## Introduction

Due to the increasing importance of representative longitudinal studies the need of sophisticated analytical modeling techniques in social sciences has risen sharply.

These techniques have a strongly interdisciplinary character: In the National Educational Panel Study (NEPS), empirical educational researchers, psychologists, and sociologists work with complex modeling techniques. In the Socio-Economic Panel (SOEP), it is predominantly political scientists, sociologists and economists who are involved in the research. Even in more substantively specific panel studies (such as Crime in the modern City (CrimoC) or the twin family study (TwinLife)), such methodological-statistical developments become more and more significant for the analysis of content related questions on course and typical developmental patterns in the samples.

No significant large longitudinal study will be assigned to exactly one field today, so that methodological basic research is of outstanding importance. The international, interdisciplinary exchange will be encouraged with this conference. The aim is to bring together methodologists working to develop methods for evaluating and addressing specific challenges of longitudinal data. In addition, application-related contributions are very welcome.

- Presentations and posters include issues from the areas of:
- Longitudinal Measurement (Non-)Invariance
- Continuous Time Modeling
- SEM and Causality
- Missing Data and Multiple Imputation
- Modelling Longitudinal Data with IRT-Models
- Bayesian Structural Equation Models with Longitudinal Data
- Moderation Effects in Latent Variables
- Causal Panel Modeling
- State-Trait Modeling
- Modeling Crime Panel Data

The Chair and the Organizing-Team wish you a good stay and exciting discussions!

*Bielefeld, March 2023*

*Jost Reinecke*

## Organizers of the conference

### Chair of ATLASS 2023

Jost Reinecke (Bielefeld University)

### Local Organizing Team:

Christina Beckord, Thomas Blank and Sylke Voß

### Scientific Board:

Rainer Alexandrowicz, University of Klagenfurt.

Kristian Kleinke, University of Siegen.

Heinz Leitgöb, Leipzig University & University of Frankfurt.

Axel Mayer, Bielefeld University.

Peter Schmidt, University of Giessen.

Daniel Seddig, University of Cologne.

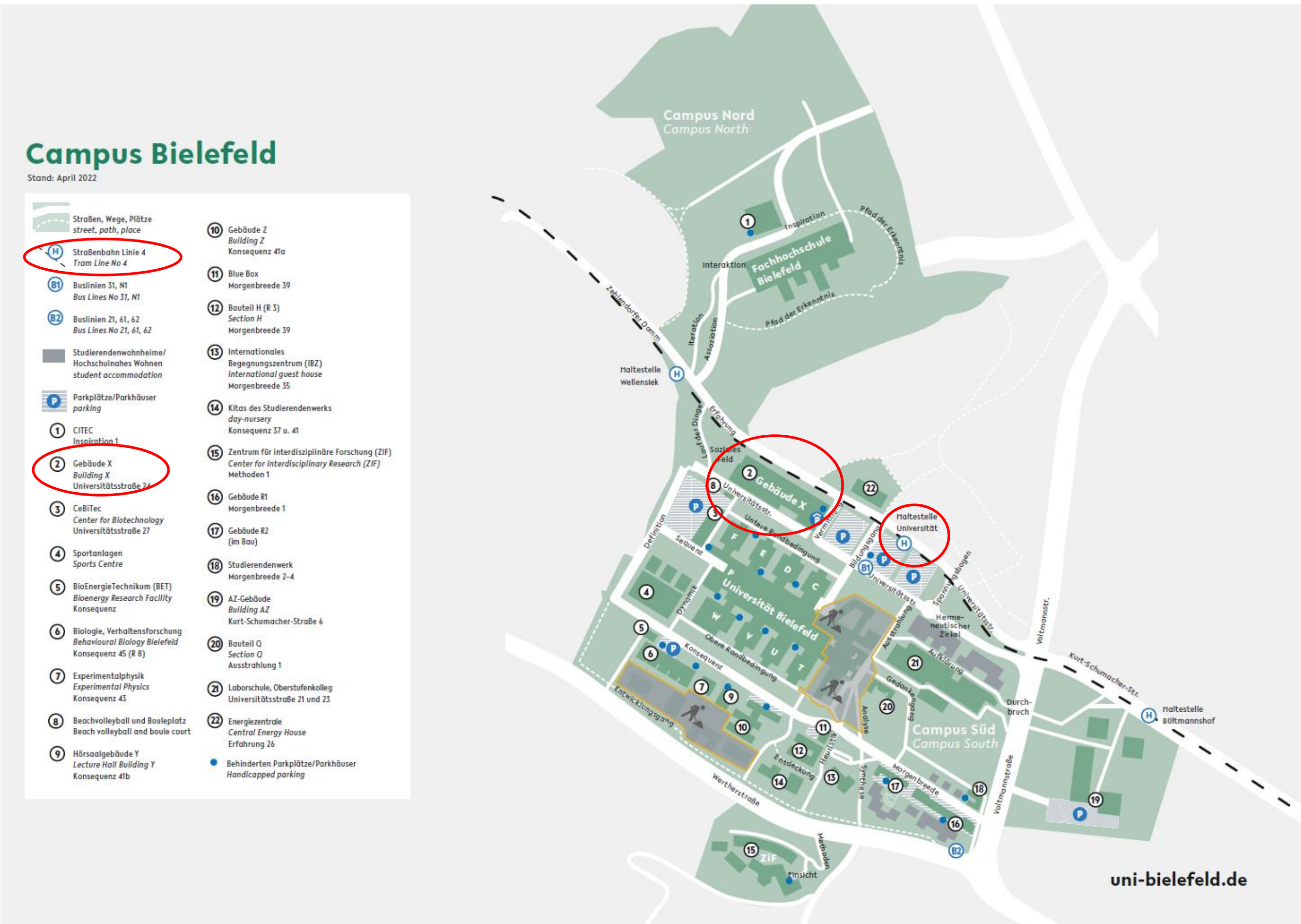
Manuel Voelkle, HU Berlin.

## Maps: Bielefeld University and the ZiF

**Due to a major construction site in the "Stapenhorststraße", the frequency of buses and the cost of cab rides may change.**

## Only for Tuesday – The X-Building:

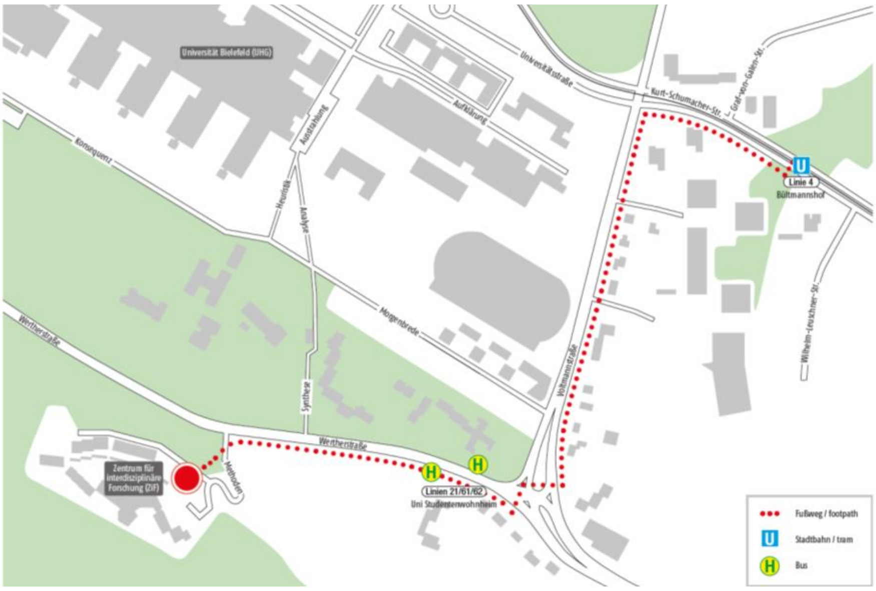
To get to the X-building you can use the stop "Universität" or the next stop "Wellensiek" as shown below



**For all other days: The ZiF**

**Due to a major construction site in the "Stapenhorststraße", the frequency of buses and the cost of cab rides may change.**

The best way to reach the ZiF from Bielefeld main station is by cab (approx. 10 min, 15 Euro). Additionally, there is a direct bus connection from the train station to the ZiF (bus stop Universität/ Studentenwohnheim, line 62 direction Borgholzhausen and line 61 direction Werther/ Halle). During the day, tram line 4 towards Universität/ Lohmannshof drives to the university every 10 minutes. From the stop Universität or Bültmannshof it is a 15-minute walk to the ZiF.



## Program Overview

| Schedule ATLASS 2023<br>**Current status: 03/10/2023** | | | | |
|---|---|---|---|---|
| Time | Tuesday,<br>03/14/2023 | Wednesday,<br>03/15/2023 | Thursday,<br>03/16/2023 | Friday<br>03/17/2023 |
| 08.30-<br>09.30 | Registration Workshop and Conference | Registration | | |
| 09.30-<br>12.30 | Pre-Conference Workshop:<br>- Craig Enders (Longitudinal Modeling and Missing Data Handling In Blimp) Room: X-C3-107<br>- Christian Geiser (Latent State-Trait Modeling with Mplus) Room: X-D2-103<br><br>Time: 09.30-13 und 14-17 | 09.30-10.00 am<br>Opening | 09.30-10.30 am<br>Keynote Craig Enders | 09.30-10.30 am<br>Keynote Fan Wallentin |
| | | 10.00-11.00 am<br>Keynote Ellen Hamaker | 10.30-11.00 am<br>Coffee Break | 10.30-11.00 am<br>Coffee Break |
| | | 11.15-12.45 am<br>Sessions<br>A-1 F-1 | 11.00-12.30 am<br>Sessions<br>C-1 E-2 | 11.00-12.30 am<br>Sessions<br>B-1 D-2 |
| 12.30-<br>13.30 | | 12.45-13.30 pm<br>Lunch | 12.30-13.30 pm<br>Lunch | 12.30-13.30 pm<br>Lunch |
| 13.30-<br>14.30 | | 13.30-14.30 pm<br>Keynote Sy-Miin Chow | 13.30-14.30 pm<br>Keynote Christian Geiser | 13.30-15:00 pm<br>Sessions<br>B-2 G2 |
| 14.30-<br>15.00 | | 14.30-15.00 pm<br>Coffee Break | 14.30-15.00 pm<br>Coffee Break | 15.15-15.45 pm<br>Closing Session |
| 15.00-<br>16.30 | | 15.00-16.30 pm<br>Sessions<br>A-2 E-1 | 15.00-16.30 pm<br>Sessions<br>D-1 C-2 | |
| 16.30-<br>18.00 | | 16.30-18.00 pm<br>Poster Session and Exhibition | 16.45-18.15 pm<br>Sessions<br>H-1 G-1 | |
| 18.15-… | | | 18.15-19.00 pm<br>Poster Session and Exhibition | |
| | | | 19.00 pm<br>Conference Dinner | |

### Topics:

A: Intensive Longitudinal Data/ Hidden Markov Model
B: Non-Linear SEM
C: Missing Data
D: Causal Panel Modeling/ Latent-State-Trait-Modeling
E: CTM/ SEM-Trees
F: Cross-Lagged-Panel Models
G: Growth Curve Modeling/ Multi-Level SEM
H: Longitudinal Measurement Invariance/ Mode Effects

### Information for all presenters;

Information for all presenters: Please come to the respective room approx. 30 minutes before your presentation in order to load your presentation onto the computer there.

It will not be possible to present with an Apple device!

## Detailed Program

**Tuesday, 03/14/2023**

! Please note that on Tuesday (and only on Tuesday) the registration for the workshops and the conference will take place in the X-building of the university and NOT in the ZiF but in the X-building of the university.

**8:30** The conference and workshop registration begins at 8:30 in room X-D2-204 (X= X-building, D2= second floor in D-section, 204= room number).

**Pre-Conference Workshops:**

**9:30-13:00 and 14:00-17:00**

**Longitudinal Modeling and Missing Data Handling in Blimp,** Room: X-C3-107

*Craig Enders*

Missing data are a ubiquitous feature of nearly all longitudinal modeling applications, arising through participant non-response, attrition, and sometimes even by design. Failure to account appropriately for missing values when conducting statistical analyses can result in badly biased estimates and incorrect inferences about the relationships under study. Longitudinal Modeling and Missing Data Handling with Blimp is a full-day workshop focused on Bayesian estimation and multiple imputation, as implemented in the Blimp software application. These procedures are advantageous because they use all available data and make realistic assumptions about the cause of missingness; estimates and significance tests are therefore valid in a broader range of situations than historical methods such as deleting incomplete data records. The purpose of this workshop is to provide participants with foundational knowledge about the application of Bayesian estimation and multiple imputation to longitudinal data analyses. To this end, the workshop will include a mix of theoretical information, practical tips, and computer demonstrations involving real world data sets. A review of mixed (multilevel) models for longitudinal data will be provided, but familiarity with this topic will be beneficial. Workshop topics are listed below.

**9:30-13:00 and 14:00-17:00**

**Latent State-Trait Modeling with Mplus,** Room: X-D2-103

*Christian Geiser*

In this applied workshop, Christian Geiser provides an introduction to latent state-trait modeling in the Mplus software. The workshop covers basic and advanced models and methods of longitudinal confirmatory factor analysis. We will discuss longitudinal measurement invariance testing and analyze models for separating trait, state residual, method, and measurement error components. Participants can bring their own laptop with the demo version of Mplus to follow the data examples.

**Wednesday, 03/15/2023**

**8:30-9:30** Registration at the service desk in the ZiF

**09:30-10:00** Opening

**10:00-11:00**
**Keynote:** Ellen Hamaker
Opportunities and challenges of intensive longitudinal data
*Chair: Jost Reinecke, "Plenarsaal", Room 222*

**11:15-12:45**

**Session A-1:** **Intensive Longitudinal Data/ Hidden Markov Models**
Chair: Heinz Leitgöb, "Plenarsaal", Room 222

Skewness and staging: Does the floor effect induce bias in multilevel AR(1) models (*Haqiqatkhah, Mohammadhossein M.; Ryan, Oisin; Hamaker, Ellen)*

Utilizing the multilevel hidden Markov model in social and behavioral data: the R CRAN package mHMMbayes and empirically based guidelines on sample size requirements (*Aarts, Emmeke; Mildiner-Moraga, Sebastian)*

A Bayesian multilevel hidden Markov model for intensive longitudinal ecological momentary assessment data of patients with bipolar disorder (*Mildiner-Moraga, Sebastian; Bruggeman, Richard; van der Krieke, Lian; Snippe, Evelien; Aarts, Emmeke)*

**Session F-1:** **Cross-Lagged Panel Models**
Chair: Daniel Seddig, "Long Table", Room 231 M

Discrete-time multistate modeling for life course analysis (*Dudel, Christian; Schneider, Daniel; Lorenti, Angelo; Myrskylä, Mikko*)

Rehabiliating the Lagged Dependent Variable with Structural Equation Modelling (*Andersen, Henrik K.; Mayerl, Jochen*)

Power analysis for the random intercept cross-lagged panel using the powRICLPM R-package (*Mulder, Jeroen*)

The appearance and duration of media effects on citizens' emotional states during the German federal elections 2021 (*Thomas, Fabian; Otto, Lukas P.; Maier, Michaela)*

Ignoring Inter-Individual Differences in Autoregressive Effects Leads to Strongly Biased Average Effect Estimates (*Jung, Alexander J.; Parrisius, Cora; Nagengast, Benjamin, Murayama, Kou*)

**12:45-13:30** **Lunch Break** (will take place in the ZiF)

**13:30-14:30**

**Keynote:** Sy-Miin Chow
Transformations of Continuous-Time Dynamic Models into Alternative Discrete-Time Models: Why, How, and Implications on Causality Inference
*Chair: Manuel Voelkle, "Plenarsaal", Room 222*

**14:30-15:00** Coffee Break

**15:00-16:30**

**Session A-2:** **Intensive Longitudinal Data and Hidden Markov Models II**
Chair: Ellen L. Hamaker, "Long Table", Room 231 M

Detecting hysteresis in psychological processes with the hysteric threshold auto-regressive (HysTAR) model (*de Jong, Daan; Ryan, Oisin, Hamaker, Ellen L.*)

How many are too many? Methods to enumerate underlying trajectories with mixture Hidden Markov Models and Sequence Analysis (*Garnier-Villareal, Mauricio; Pavlopoulos, Dimitris*)

Employment trajectories in the presence of measurement error. An application using Mixed Hidden Markov Models. (*Pavlopoulos, Dimitris; Garnier-Villareal, Mauricio)*

**Session E-1:** **Continuous-Time Modeling I**
Chair: Johan H.L. Oud, Room: "Plenarsaal", Room 222

Latent Variable Forests: Estimating Latent Variable Scores From Conditionally Causal Models (*Classe, Franz; Kern, Christoph)*

Visualizing Heterogeneity and Stabilty of Structural Equation Model Trees for Longitudinal Data (*Arnold, Manuel; Strobl, Carolin; Debelak, Rudolf; Voelkle, Manuel; Brandmaier, Andreas M.)*

Continuous-time SEM trees and forests: A score-based approach (*Cáncer, Pablo F.; Arnold, Manuel; Estrada, Eduardo; Voelkle, Manuel)*

On Regularized Continuous and Discrete Time Structural Equation Models (*Orzek, Jannik H.)*

**16:30-18:00** Poster Session and Exhibition

**Thursday, 03/16/2023**

**9:30-10:30**
**Keynote:** Craig Enders
Longitudinal Modeling and Missing Data Handling In Blimp
*Chair: Kristian Kleinke "Plenarsaal", Room 222*

**10:30-11:00** **Coffee Break**

**11:00-12:30**

**Session C-1:** **Multiple Imputation with Longitudinal Data I**
Chair: Simon Grund, "Plenarsaal", Room: 222

Multiple imputation of missing data in longitudinal analyses with many variables *(Grund, Simon; Lüdtke, Oliver; Robitzsch, Alexander)*

Robust multiple imputation based on quantile forests *(Kleinke, K.; Fritsch, M.)*

Multiple imputiation of incomplete panel data based on a piecewise growth curve model *(Kleinke, Kristian; Reinecke, Jost)*

**Session E-2:** **Continuous-Time Modeling II**
Chair: Manuel Voelkle, "Long Table" Room: 231 M

Some remarks about the history and philosophical background of continuous time modeling in social science *(Oud, Johan H.L.)*

A moderator variable approach to control for cohort differences in accelerated longitudinal designs *(Cáncer, Pablo F.; Ferrer, Emilio; Estrada, Eduardo)*

Continuous-Discrete Filtering using the Duncan-Mortensen-Zakai (DMZ) Equation: Smooth Likelihood Surface *(Singer, Hermann)*

**12:30-13:30** **Lunch Break** (will take place in the ZiF)

**13:30-14:30**
**Keynote:** Christian Geiser
Latent state-trait analysis: State of the art and future directions
*Chair: Axel Mayer "Plenarsaal", Room 222*

**14:30-15:00** **Coffee Break**

**15:00-16:30**

**Session D-1:** **Causal Inference and Causal Mediation**
Chair: Daniel Seddig, "Plenarsaal", Room: 222

Causal Effect Estimation in Large-Scale Assessment Data: Using a Multi-Group Structural Equation Model with Categorical Indicators in EffectLiteR *(Sengewald, Marie-Ann; Mayer, Axel)*

Stochastic covariates-based treatment effects from non-linear regression models *(Kiefer, Christoph)*

A simulation study of different approaches to mediation analysis in presence of unobserved heterogeneity and reverse causality *(Becker, Dominik)*

The Parametric g-Formula for Latent Markov Models *(Clouth, Felix J.; Bijlsma, Maarten J.; Pauws, Steffen; Vermunt, Jeroen K.)*

**Session C-2:** **Multiple Imputation with Longitudinal Data II**

Chair: Kristian Kleinke, "Long Table", Room: 231 M

Imputation of missing longitudinal data using the broken stick model *(van Buuren, Stef)*

The Performance of Multiple Imputation in Social Surveys with Missing Data from Planned Missingness and Item Nonresponse *(Axenfeld, Julian)*

**16:45-18:15**

**Session H-1:** **Measurement Invariance and IRT-Modeling**
Chair: Heinz Leitgöb, "Plenarsaal", Room: 222

The decomposition of true change and response shifts in latent constructs across time *(Leitgöb, Heinz; Seddig, Daniel)*

Assessing Individual Change with Item Response Models *(Alexandrowicz, Rainer; Keller, Ferdinand)*

Alignment of longitudinal models *(Asparouhouv, Tihomir)*

**Session G-1:** **Growth Curve and Multi-Level Modeling I**
Chair: Thomas Blank, "Long Table", Room: 231 M

Recent advances in accelerated longitudinal designs to study psychological development *(Estrada, Eduardo)*

Specifying composites in growth curve analysis *(Yu, Xi; Schuberth, Florian; Henseler, Jörg)*

Examining Nonlinear Science Achievement Growth Using Early Childhood Longitudinal Study-Kindergarten 2011 *(Reid, Tingting)*

**18:15-19:00** **Poster Session and Exhibition**

**19:00** **Conference Dinner** (will take place in the ZiF)

**Friday, 03/17/2023**

**09:30-10:30**

**Keynote:** Fan Y. Wallentin
A Marginal Maximum Likelihood Approach for Extended Quadratic Structural Equation Modeling with Ordinal Data
*Chair: Peter Schmidt, "Plenarsaal", Room 222*

**10:30-11:00** **Coffee Break**

**11:00-12:30**

**Session B-1:** **Non-linear Structural Equation Modeling**
Chair: Yves Rosseel, "Plenarsaal", Room: 222

Latent moderation with many predictors and simultaneous equation systems: Comparison and application of Latent Moderated Systems (LMS), Product Indicator (PI) approaches and Structural after measurement approach (SAM) using the example of an empirical study *(Diehl, Yannick; Schmidt, Peter)*

Estimating Power in Moderated Mediation Models and Ecogenous Moderation Model: The pwrModMed R-package *(Irmer, Julien P.; Klein, Andreas G.; Schermelleh-Engel, Karin)*

Cause for Concern: Omitted Cross-Loadings in Measurement Models of Nonlinear Structural Equation Models *(Navarro, Karina; Schermelleh-Engel, Karin)*

**Session D-2:** **(Causal) Panel Modeling and Applications**
Chair: Christina Beckord, "Long Table", Room: 231 M

Does loneliness contribute to psychological distress? A longitudinal analysis using data from the Understanding Society Panel Study 2017-2021 *(Seifert, Nico)*

A Critical Look at the Benefits and Drawbacks of Residual-Level Approach to Cross-Lagged Panel Models *(Andersen, Henrik K.)*

Examining Parameter Differences in Latent State-Trait Models: Modeling Loneliness During Covid-19 Lockdowns Using a Bayesian Moderated Nonlinear Latent State-Trait Approach *(Münch, Fabian, Freitag, Julia; Mund, Marcus; Koch, Tobias)*

Whose generalized trust is shattered by criminal victimization? Using various methods to study heterogenous causal effects *(Kaiser, Florian)*

Integrating complex panel data models into dynamic microsimulations: an application to the analysis of the migrant and gender pay gaps in Germany *(Bekalarczyk, Dawid; Depenbrock, Eva; Frohn, Christoph; Obersneider, Monika)*

**12:30-13:30** Lunch Break

**13:30-15:00**

**Session B-2:** **Non-Linear Structural Equation Modeling and Mode Effects**
Chair: Peter Schmidt, "Plenarsaal", Room: 222

A structural-after-measurement (SAM) approach for latent moderation *(Rosseel, Yves)*

A small sample correction for factor score regression *(Bogaert, Jasper; Loh, Wen Wie; Rosseel, Yves)*

Estimating Mode Effects in Panel Surveys: A Multitrait Multimethod Approach *(Kroh, Martin; Karmann, Anna; Kühne, Simon)*

**Session G-2:** **Growth Curve and Multi-Level Modeling II**
Chair: Jost Reinecke, "Long Table", Room: 231 M

On evaluating the performance of model fit and selection indices for Bayesian piecewise growth modeling: The effect of model misspecification and missing data *(Heo, Ihnwhi; Jia, Fan; Depaoli, Sarah)*

Analyzing the development of legal norm acceptance by using a Bayesian second-order growth model with approximate measurement invariance. *(Bendler, Jasper)*

Modelling two time-varying indicators measured in real-life-teachers' physiological stress and affect *(Jögi, Anna-Liisa; Malmberg, Lars-Erik, Pakarinen, Eija; Lerkkanen, Marja-Kristiina)*

**15:15-15:45** **Closing Session,** "Plenarsaal", Room: 222

# ABSTRACTS

**Wednesday, 10:00-11:00, Keynote Ellen Hamaker,** Chair: Jost Reinecke, "Plenarsaal", Room 222

## Opportunities and challenges of intensive longitudinal data

Ellen L. Hamaker

*Utrecht University, Faculty of Social and Behavioural Sciences,*

*Department of Methodology and Statistics*

Technological developments like smart phones and activity trackers have made it relatively easy to obtain many repeated measures from large samples of people while they are living their daily life. Measures may include self-report on affect, behaviors, cognitions, and the environment, but also physiological and/or non-intrusive measurements throughout the day.
Such intensive longitudinal data offer new opportunities for studying the dynamics of everyday processes, and allow researchers to pose new research questions. However, with these new opportunities also come new challenges: How should we measure a process—e.g., how often and at what rate should we measure it—and what model should we use to analyze the data—e.g., how can we link our model to our research question? In this talk I will discuss opportunities and challenges associated with this exciting new methodology, and sketch various ways in which we may move forward.

**Wednesday, 11:15-12:45, Session A-1: Intensive Longitudinal Data/ Hidden Markov Models.**
Chair: Heinz Leitgöb, “Plenarsaal”, Room 222

## Skewness and staging: Does the floor effect induce bias in multilevel AR(1) models?

Mohammadhossein Manuel Haqiqatkhah, Oisin Ryan & Ellen L. Hamaker

*Utrecht University, Faculty of Social and Behavioural Sciences, Department of Methodology and Statistics*

***Keywords:*** Floor effect; Experience sampling method; Emotional inertia; Staging effect; Non-Gaussian time series

In the past two decades, the collection of intensive longitudinal data has become increasingly popular in psychological research. To study the dynamics in these data, the multilevel versions of the őrst-order autoregressive (AR(1)) model are often used. It has been suggested that individuals with more severe stages of mental disorders tend to have stronger autoregressions and cross-regressions among certain affective and psychopathology symptom measures. This phenomenon has been referred to as the staging effect.

Two of the main assumptions of the multilevel AR(1) model are level-1 and level-2 normality, which require that individual time series and sample means be normally distributed. However, these two assumptions are often violated in empirical data; importantly, healthier individuals, at many time instances, tend to score very low on negative emotions and symptoms, leading to the floor effect - that is, a high percentage of the responses are equal, or very close, to the lowest value on the scale - which is accompanied by less variability and high skewness.

Using a large-scale simulation study, we investigate the effect of skewness on the estimated autoregressive parameter in the multilevel AR(1) model. To do so, we őrst provide ways of detecting and characterizing the floor effect in empirical data. We then introduce three novel time series models that can generate skewed continuous and discretevalued responses (for Likert scales and counts data). Finally, we discuss the simulation study we preformed to answer our research question, in which we analyzed these data using the multilevel AR(1) model with fixed and random residual variance. The results indicate that using the more conventional model (with őxed residual variance) leads to negative bias, whereas using the more flexible model (with random residual variance) produces positive bias in the estimated autoregression. We discuss the implications of our study for choosing modeling approaches and data collection.

# Utilizing the multilevel hidden Markov model in social and behavioral data: the R CRAN package mHMMbayes and empirically based guidelines on sample size requirements

Emmeke Aarts & Sebastian Mildiner-Moraga

*Utrecht University, Faculty of Social and Behavioural Sciences,*

*Department of Methodology and Statistics*

***Keywords***: Hidden Markov model, Multilevel modeling, Bayesian estimation, Intense longitudinal data

The multilevel (also known as mixed or random effects) hidden Markov model - a generalization of the hidden Markov model (HMM) - is a promising vehicle to investigate latent dynamics over time in social and behavioral processes in intense longitudinal data. The multilevel HMM is tailored to accommodate data of multiple individuals simultaneously, allowing for heterogeneity in the model parameters (transition probability matrix and conditional distribution), while estimating one overall HMM. Hence, the multilevel framework facilitates the study of individual-specific trajectories and the study of individual differences.

An open-source implementation of the multilevel hidden Markov model is provided by the R CRAN package mHMMbayes. The model can be fitted on multivariate data with a categorical or normal (i.e., Gaussian) distribution, and include individual level covariates (allowing for e.g., group comparisons on model parameters). Parameters are estimated using Bayesian estimation utilizing the forward-backward recursion within a hybrid Metropolis within Gibbs sampler. The package also includes various visualization options, a function to simulate data, and a function to obtain the most likely hidden state sequence for each individual using the Viterbi algorithm.

In addition, we provide guidelines on sample size requirements - currently still lacking for typical social and behavioral data in combination with the multilevel HMM. The guidelines are based on extensive simulation studies and are driven by the complexity of the data and the study objectives of the practitioners.

**Wednesday, 11:15-12:45, Session A-1: Intensive Longitudinal Data/ Hidden Markov Models.**
Chair: Heinz Leitgöb, "Plenarsaal", Room 222

## A Bayesian multilevel hidden Markov model for intensive longitudinal ecological momentary assessment data of patients with bipolar disorder

Sebastian Mildiner-Moraga[1)], Fionneke M. Bos[2,3)], Bennard Doornbos[4)], Richard Bruggeman[2)], Lian van der Krieke[2)], Evelien Snippe[3)] & Emmeke Aarts[1)]

*[1)]Utrecht University, Faculty of Social and Behavioural Sciences, Department of Methodology and Statistics*
*[2)]University of Groningen, University Medical Centre Groningen, Rob Giel Research Centre, Department of Psychiatry, Groningen, The Netherlands*
*[3)]University of Groningen, University Medical Centre Groningen, Interdisciplinary Centre Psychopathology and Emotion Regulation (ICPE), Department of Psychiatry, Groningen, The Netherlands*
*[4)] Lentis Research, Lentis Psychiatric Institute, Groningen, The Netherlands*

***Keywords:*** Hidden Markov model, multilevel modeling, experience sampling method, bipolar disorder

In Bipolar disorder (BD), recognizing and quantifying mood and mood instability may improve care and calls for high-frequency measures coupled with advanced statistical models. We present a multilevel hidden Markov model (HMM) with a Gaussian emission distribution to identify mood states and accommodate heterogeneity between patients using continuous random intercepts. The multilevel HMM was applied to 4-month ecological momentary assessment (EMA) data in twenty patients with BD. EMA data comprised self-reported questionnaires (5 per day) measuring manic and depressive constructs using 12 items. Manic and depressive symptoms were further assessed by weekly administered self-reported questionnaires (i.e., Altman Self-Rating Mania Scale and Quick Inventory for Depressive Symptomatology Self- Report). Alignment between uncovered mood states and weekly questionnaires was assessed with a multilevel linear model. The multilevel HMM uncovered four mood states (euthymic, manic, mixed, and depressive) that aligned with weekly symptom scores. On average, the duration of the states was <24h, and states switched more frequently than weekly data suggested. In almost half of the patients, significant mood instability was observed. Large individual differences were observed in state duration and switching. The results show that datadriven identifcation of mood dynamics through a multilevel HMM is a promising method for improved diagnosis of clinical subtypes and treatment selection. Quantifying mood instability has the potential to improve the care of patients with bipolar disorder on a very individual scale.

**Wednesday, 11:15-12:45, Session F-1: Cross-Lagged Panel Models.** Chair: Daniel Seddig, "Long Table", Room 231 M

## Discrete-time multistate modeling for life course analysis

Christian Dudel[1,2], Daniel Schneider[1], Angelo Lorenti[1] & Mikko Myrskylä[1,3]

[1] *Max Planck Institute for Demographic Research, Rostock, Germany*
[2] *Federal Institute for Population Research, Wiesbaden, Germany*
[3] *University of Helsinki, Finland*

***Keywords:*** Multistate modeling, life course analysis, discrete-time modeling, panel data, Markov assumption

Many social processes can be represented by individuals being in, and transitioning between, a finite number of states. Examples include transitions in the labor market, between marital states, and many more. Statistical modelling of such processes can be done using multistate models. Multistate models come in two different variants: discrete-time and continuous-time. While continuous-time multistate models have been extensively described in the literature, there is little guidance on their discrete-time counterparts. This is unfortunate since many data sources – regularly spaced longitudinal surveys in particular – naturally lend themselves to modelling in discrete time.

We provide new theoretical and practical insights into discrete-time multistate models (DTMMs) for panel data. From a theoretical perspective, we establish a set of theoretical estimands which can be studied using DTMMs and which are linked to life course theory and the concept of cumulative (dis)advantage. Moreover, we present novel technical results which counter one of the main criticisms of multistate modeling: multistate models usually rely on the Markov assumption, which implies that the studied process is memoryless. While this assumption likely is false for many potential applications, we show that several quantities can be consistently estimated using DTMMs even if the Markov assumption does not hold. Finally, related to the previous two points, we argue that DTMMs can provide adequate representations of population-level quantities, while being less well-suited for individual-level predictions.

From a practical perspective, we use data from SHARELIFE to show that DTMMs provide good representations of real-word data, and that finite sample bias is modest. An in-depth example is provided using data from the U.S. Health and Retirement Study. Finally, we briefly remark on a novel Stata package and existing R packages for the estimation of DTMMs.

**Wednesday, 11:15-12:45, Session F-1: Cross-Lagged Panel Models.** Chair: Daniel Seddig, "Long Table", Room 231 M

## Rehabilitating the Lagged Dependent Variable with Structural Equation Modeling

Henrik Kenneth Andersen & Jochen Mayerl

*Chemnitz University of Technology, Institute of Sociology*

***Keywords***: causal analysis, panel analysis, cross-lagged panel models, autoregression, collider bias

There is a long history of including the lagged dependent variable in panel models, especially in the structural equation modeling framework. These include, but are not limited to, cross-lagged panel models, for example.

However, it is often argued that this practice is ill-advised. Namely, in the presence of time-invariant unobserved heterogeneity, the inclusion of the lagged dependent variable is said to open up unintended back-door paths and bias the estimates of the causal variable. Much existing literature therefore recommends avoiding lagged dependent variable models.

We show that panel analysis in the structural equation modeling framework is generally not affected by this issue. Including the lagged dependent variable has the benefit of closing back-door paths due to unobserved time-varying confounders. The existence of time-invariant unobserved confounders is unproblematic.

We demonstrate this using simulated data and argue that the broad use of cross-lagged panel models is legitimate and these models can provide benefits compared to models that do not include the lagged dependent variable.

**Wednesday, 11:15-12:45, Session F-1: Cross-Lagged Panel Models.** Chair: Daniel Seddig, "Long Table", Room 231 M

## Power analysis for the random intercept cross-lagged panel using the powRICLPM R-package

Jeroen D. Mulder

***Keywords:*** random intercept cross-lagged panel model, power, R-package, stable trait autoregressive trait state model

The random intercept cross-lagged panel model (RI-CLPM) is a popular model among psychologists for studying reciprocal effects in longitudinal panel data. It extends the traditional cross-lagged panel model (CLPM) by separating stable (for the duration of the study), between-unit variance from fluctuating, within-unit variance. Autoregressive effects can then be interpreted as purely within-unit effects and carry-over (rather than estimates of stability of the rank-order of units, as is the case in the CLPM), and cross-lagged effects can then be interpreted as the within-unit effect or "spillover" of one domain into another.

A frequently asked question by substantive researchers in relation to the RI-CLPM, is about the required sample size for detecting hypothesized effects. Although various texts and software packages have been published concerning power analyses for structural equation models (SEM) generally, none have proposed a power analysis strategy that is tailored to the particularities of the RI-CLPM. This can be problematic because mismatches between the power analysis design, the model, and reality, can negatively impact the validity of the recommended sample size and number of repeated measures.

As power analyses play an increasingly important role in the preparation phase of research projects, this presentation proposes and demonstrates a 6-step Monte Carlo power analysis strategy that is tailored to the RI-CLPM. The strategy is created with usability for applied researchers in mind and is implemented in the R-package powRICLPM. The presentation focuses on the (basic) bivariate RI-CLPM, as well as extensions to include various (stationarity) constraints over time, measurement error (leading to the stable trait autoregressive trait state model), and non-normal data, and the usage of bounded estimation to prevent non-convergence.

**Wednesday, 11:15-12:45, Session F-1: Cross-Lagged Panel Models.** Chair: Daniel Seddig, “Long Table”, Room 231 M

## The appearance and duration of media effects on citizens’ emotional states during the German federal elections 2021

Fabian Thomas, Lukas P. Otto, Michaela Maier

***Keywords:*** effect patterns, appearance and duration of effects, cross-lagged panel models

One key idea of the social sciences is investigating the (causal) effect of one variable on another. Implicitly, scholars often assume these effects to appear immediately. However, this might be a simplistic idea – effects can be dynamic and follow a particular development over time. For example, in communication science it was shown that media effects usually appear in immediate, delayed, or cumulative patterns over time. Once established, they vanish quickly, decrease over time, or show a continuous impact.

While literature in statistical modeling presented many approaches that accurately link two variables over time and dynamically assess effects from one variable on another, approaches discussing how to identify specific patterns in the appearance and duration of such effects are rare. Recently, however, a methodological approach was presented that allows to identify patterns in the development of effects over time building on well-established statistical models (i.e. the random intercept cross-lagged panel model) and traditions of time-series analysis. The idea is to sucessively add lagged predictors to the model until an effect appears and then to continue the process until the effect disappears allowing to identify effect patterns.

The aim of this paper is to apply this framework in order to identify dynamic media effects of negative political information on citizens’ emotional states. In particular, we use data from a mobile experience sampling study conducted during the four weeks before the German federal elections in 2021 and a corresponding media content analysis (N=247). Based on this data, we identify and compare several effects patterns and show how the RI-CLPM can be extended to investigate the relationship between negative political information and emotions. Further, we discuss the relevance of the approach for other fields in social science

**Wednesday, 11:15-12:45, Session F-1: Cross-Lagged Panel Models.** Chair: Daniel Seddig, “Long Table”, Room 231 M

## Ignoring Inter-Individual Differences in Autoregressive Effects Leads to Strongly Biased Average Effect Estimates

Alexander J. Jung[1)], Cora Parrisius[1,2)], Benjamin Nagengast[1)] & Kou Murayama[1)]

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Autoregressive effects are frequently estimated in a plethora of models for the analysis of longitudinal data. For example, they are often estimated in longitudinal structure equation modelling (SEM) to account for stability in a construct that cannot be explained by other predictors in the model (e.g., Biesanz, 2012). However, in some cases, the stability of a construct differs between individuals depending on unobserved person-specific characteristics. For example, individuals with bipolar tendencies may exhibit more frequent mood changes and, therefore, show a lower stability in longitudinal measures of their mood than the average. In such cases, the multilevel SEM framework is usually employed to estimate random autoregressive effects with a mean and a standard deviation (e.g., Raudenbush & Bryk, 2002).

Using simulated data, we show that in such cases estimating random autoregressive effects leads to strongly biased average effect estimates if two or more consecutive autoregressive effects are estimated. This is because individuals who show lower (higher) stability in a construct between the first two measurement occasions also show lower (higher) stability between subsequent measurements – An information that is not modelled in traditional multilevel-SEM. Our results show that observed biases in autoregressive parameter estimates increase with higher means and higher variances of the true autoregressive-effect vectors, with higher correlations between the vectors of the true average effects, and with a higher number of modelled measurement occasions.

It is well known that misspecifications of one part of a model usually lead to problems in other parts of a model as well (e.g., Olsson et al., 2000). Thus, we assume that disregarding potential correlated effect vectors in SEM may be an issue that biases many effect estimates in current research practice.

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**Wednesday, 13:30-14:30, Keynote Sy-Miin Chow,** Chair: Manuel Voelkle, “Plenarsaal”, Room 222

## Transformations of Continuous-Time Dynamic Models into Alternative Discrete-Time Models: Why, How, and Implications on Causality Inference

Sy-Miin Chow

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Irregularly spaced longitudinal data often arise in experience sampling studies that use partially random sampling intervals to capture the participants’ status in the moment. Many structural equation modeling (SEM) approaches for fitting longitudinal or dynamic models to intensive longitudinal data treat the time intervals between successive occasions as equally spaced (e.g., in computing lagged covariance or correlation matrices for model fitting purposes) and are not well suited for use with irregularly spaced data. Several authors have introduced continuous-time models in the form of linear stochastic differential equation (SDE) models as a way to accommodate such irregularly spaced time intervals, and discussed their parallels with the SEM framework. Unfortunately, the relations between SDEs and their discrete time counterparts, such as vector autoregression (VAR) and structural VAR (SVAR) models adopted broadly in dynamic network analyses, are not well understood, leading at times to misconceptions of these alternative formulations as completely distinct modeling options. In this talk, we present and discuss the relations and transformation functions for mapping linear SDE models to VAR and SVAR, and implications on causality inference. Code and demonstrations for fitting these models to irregularly spaced data using an R package, dynr, are provided, followed by discussions of some of the caveats, challenges, and possible extensions to leverage these transformations to fit continuous-time dynamic network models.

**Wednesday, 15:00-16:30, Session A-2: Intensive Longitudinal Data and Hidden Markov Models II.** Chair: Ellen Hamaker, “Long Table”, Room 231 M

## Detecting hysteresis in psychological processes with the hysteretic threshold autoregressive (HysTAR) model

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***Keywords:*** Hysteresis; Regime Switching; Threshold autoregressive model

The presence of different regimes characterizes many psychopathological phenomena. Switches between these regimes are hysteretic when the “tipping point” of a switch depends on the current regime itself. This implies that a regime switch is not immediately reversible, even when the cause of the switch is reversed. Although this principle is very intuitive and found in wide range of phenomena, applications in the social sciences have been limited because of modeling difficulties associated with differential equation models. The current study introduces the hysteretic threshold autoregressive (HysTAR) model, first proposed in the econometric literature. Inspired by the threshold autoregressive (TAR) model, regime switches are determined by the value of an observed threshold variable. However, unlike in the TAR model, two tresholds are specified, between which the regime will not switch. The current study implements the BAR model in the R package bar, with a simulation function and conditional least squares estimation of the model parameters. The model is applied in a small simulation study and an empirical psychopathological example.

**Wednesday, 15:00-16:30, Session A-2: Intensive Longitudinal Data and Hidden Markov Models II.** Chair: Ellen Hamaker, “Long Table”, Room 231 M

## How many are too many? Methods to enumerate underlying trajectories with Mixture Hidden Markov Models and Sequence Analysis

Mauricio Garnier-Villarreal Dimitris Pavlopoulos

*Vrije Universiteit Amsterdam*

Typological analysis of longitudinal data, i.e. classifying sequences of data from different individuals for a particular phenomenon, is becoming increasingly popular in social sciences. When we have longitudinal data, a main focus is to describe the longitudinal pattern, like the slope in growth curve and the transition matrix in Markov models. Conclusions about these patterns might be incorrect if there is group heterogeneity, meaning that subgroups of subjects present different longitudinal patterns (trajectories). Here we focus on methods that can detect this heterogeneity when the phenomena of interest is categorical, like Mixture Hidden Markov Models (MHMM) and Sequence Analysis (SA). The issue of class enumeration is not new, but most of the research has been done in cross-sectional models, and when looking at longitudinal models some focus has been done in with growth mixture models, where the phenomena is continuous in nature. With a simulation study, we evaluate methods to select the correct number of trajectories. For SA, we will compare the measures of the quality of a partition described by Studer (2013), and for MHMM we will compare the information criteria commonly used for class enumeration such as AIC, BIC (Masyn, 2013), and tests like BLRT (McNeish & Harring, 2017). We test these methods across the conditions of number of true trajectories, level of overlap, trajectory types, and unbalance samples. With those conditions we intend to evaluate the methods across realistic data conditions. We will present our simulation results, and recommendations for applied researchers in how to detect group heterogeneity in longitudinal patterns. This way we are able to properly describe longitudinal pattern heterogeneity.

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## Employment trajectories in the presence of measurement error. An application using Mixed Hidden Markov Models

Dimitris Pavlopoulos   Mauricio Garnier-Villarreal

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Inspired by the work of Abbott (1983) social scientists attempt more and more often to describe and explain social phenomena using a processual approach. In more detail, researchers produce sequence typologies of employment status (Mattijssen & Pavlopoulos, 2019) or marital status (Elzinga & Liefbroer, 2007). This research has ignored so far the presence of measurement error in the data that is used. Even rich register data – that are highly suitable to analyse trajectories – contain measurement error due to administrative delays, reporting errors and failing software. Research has shown that this error can have severe consequences on the estimation of transition rates (Pavlopoulos & Vermunt, 2015) but can also bias typologies that result from processual approaches (Garnier-Villarreal & Pavlopoulos, 2022). In this paper, we propose a Mixed Hidden Markov Model that can simultaneously correct for random and systematic misclassification error in different (non)employment statuses and types of employment contract and classify (error-corrected) employment trajectories into different clusters. This model is applied on a unique register dataset with information on individuals living in the Netherlands from 2007 until 2015.

Our results confirm that measurement error can bias mobility measures: almost half of the observed transitions from employment with a fixed-term contract to a permanent contract and from employment with temporary work agencies or with an on-call contract to a permanent contract is due to misclassification error. Results show further the existence of 10 clusters (mixtures) that differ considerably both in the latent initial state probabilities and in the latent transition probabilities. 4 of these states can be rather seen as 'noise' states as they are extremely small and have erroneous transition probabilities. The other 6 clusters correspond to different segments of the labour market with different patterns of moving to or out of insecure employment and non-employment.

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**Wednesday, 15:00-16:30, Session E-1: Continuous-Time Modeling I.** Chair: Han Oud, "Plenarsaal", Room 222

## Latent Variable Forests: Estimating Latent Variable Scores From Conditionally Causal Models

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***Keywords:*** machine learning, MIRT, DIF, latent variable scores

We develop a latent variable forest (LV Forest) algorithm for the estimation of latent variable scores from conditionally causal models with one or more latent variables. LV Forest establishes conditional causality in confirmatory factor analysis (CFA) models with ordinal and/or numerical response variables. Furthermore, the algorithm estimates latent variable scores for the conditionally causal models. Through parametric model restrictions together with a non-parametric tree-based machine learning approach, LV Forest estimates latent variables scores that fulfill the main criteria for (conditional) construct validity (see APA, 2014).

SC Forest draws on the SEMTree approach (Arnold et al., 2021; Brandmaier et al., 2013) in order to grow trees that detect heterogeneity in model parameter estimates. In building a tree ensemble, LV Forest utilizes random split selection and bagging akin to the random forest algorithm by Breiman (2001) to increase tree diversity. For the estimation of parameters of conditionally causal models, we test for conditional stability of the latent variable's measurement paths using the generalized M-fluctuation test (Zeileis & Hornik, 2007). LV Forest eventually computes individual predictions of the latent variable scores for each iteration (i.e. each tree). Only those subgroups for which conditional causality in the models can be established are used for prediction. The individual predictions are then averaged across all trees.

In the context of latent state-trait modeling (Steyer et al., 2015), individual item difficulties may be estimated through item-eect variables (Classe & Steyer, 2022; Thielemann et al., 2017). However, item parameters of such longitudinal IRT models may still differ between subgroups in the population. Thus, the estimation of valid latent variable scores for latent trait models with latent item-effect variables could be improved through LV Forest.

We apply LV Forest to simulated data and show that for a latent state-trait model, parameter heterogeneity and subgroups with unconfounded measurement paths can be detected by the algorithm. Furthermore, prediction accuracy of the latent variable scores of the model is increased through LV Forest.

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**Wednesday, 15:00-16:30, Session E-1: Continuous-Time Modeling I.** Chair: Han Oud, "Plenarsaal", Room 222

## Visualizing Heterogeneity and Stability of Structural Equation Model Trees for Longitudinal Data


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***Keywords***: structural equation models, recursive partitioning, heterogeneity, longitudinal data



Structural equation model (SEM) trees combine the strengths of SEMs as a confirmatory multivariate analysis technique and recursive partitioning as a data-driven method to identify homogeneous groups of individuals. SEM trees find covariates and covariate interactions that predict group differences in SEM parameters by forming a tree structure that recursively separates a data set into subsets. While SEM trees are relatively easy to interpret, modifying a SEM based on a given tree can be challenging. Typically, SEM trees split the data by allowing all SEM parameters to vary between groups, making it hard to identify which parameters are affected by the covariate and which parameters are not. In this talk, we will demonstrate how SEM trees can be used to identify parameter heterogeneity in contemporary models for longitudinal data using the R package semtree. Furthermore, we will show novel graphical representations of parameter heterogeneity that may guide model modification. In addition, we present further descriptive measures and plots to assess the stability of covariate and cutpoint selection.

**Wednesday, 15:00-16:30, Session E-1: Continuous-Time Modeling I.** Chair: Han Oud, "Plenarsaal", Room 222

## Continuous-time SEM trees and forests: A score-based approach

Pablo F. Cáncer, Manuel Arnold, Eduardo Estrada, Manuel Voelkle

***Keywords:*** continuous time analysis, recursive partitioning, score-based tests, structural equation modelling, heterogeneity.

Purpose. Model-based recursive partitioning has been gaining traction in psychological research. The technique finds similar individuals in heterogeneous data sets and identifies the most important predictors of group differences in the process. In the past decade, structural equation models (SEM) have been almost entirely partitioned using the semtree software package, leading to so-called SEM trees and forests. Recently, score-based covariate testing has been implemented into semtree, drastically improving runtime and making the partitioning of more complex models possible. This talk shows how semtree can be leveraged to analyze between-individual heterogeneity in dynamic panel models, focusing on continuous-time (CT) models. Unlike discrete-time (DT) models, CT models adapt effortlessly to longitudinal data observed with different time intervals between measurements. Thus, our resulting approach, which we call score-based CTSEM trees, is well suited to deal with heterogeneity between individuals and measurement occasions and can be computed quickly.

Method. We linked semtree to the ctsem package, used to estimate CT models. Through a Monte Carlo study, we examined the performance of CT-SEM trees and forests under a broad set of empirically relevant conditions.

Results and discussion. We discuss the most relevant findings, elaborate on the strengths and limitations of the proposed algorithm, and comment on current challenges and future lines of research in the context of between-individual differences in change.

**Wednesday, 15:00-16:30, Session E-1: Continuous-Time Modeling I.** Chair: Han Oud, "Plenarsaal", Room 222

## On Regularized Continuous and Discrete Time Structural Equation Models

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***Keywords:*** regularization, lasso, continuous time structural equation model, cross-lagged panel model

There is an increasing use of regularization methods in structural equation modeling. Regularization methods can improve the predictive performance as compared to maximum likelihood estimates, while also removing unnecessary parameters. A promising use case are the recently proposed continuous time network models (Ryan & Hamaker, 2021). They capture dynamical processes by means of continuous time structural equation modeling which allows for refined centrality measures and irregularly sampled data. However, the resulting models can have dozens of parameters, are therefore difficult to interpret and tend to overfit in small samples. We show that combining regularization techniques with continuous time network models can provide a remedy, resulting in better predictive performance and improved sparsity in both, time series data (N = 1) and panel data (N > 1) (Orzek & Voelkle, in press). We demonstrate how to implemented the method in the R package regCtsem and the more flexible lessSEM package that allows for user-defined parameter transformations. To highlight the versatility of lessSEM, we additionally show an approximate measurement invariance procedure inspired by Bayesian cross-lagged panel models (e.g., Liang, Yang, & Huang, 2018). Here, regularization can be used to capture sudden changes in parameter estimates indicating, for instance, a regime switch.

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**Poster Session, Wednesday, 16:30-18:00 AND Thursday, 18:15-19:00**

## Avoiding nonconvergence in small sample SEM using an adjusted variance-covariance matrix

Julie de Jonckere & Yves Rosseel

*Department of Data Analysis, Ghent University, Belgium*

The problems that arise when SEM is used in settings where the sample size is small have been known for a long time. Indeed, small sample SEM is prone to problems such as extreme parameter values, biased point estimates, negative variances, unreliable p-values, or nonconverged solutions (Bentler & Yuan, 1999; Nevitt & Hancock, 2004). Over the years, a number of solutions have been put forward that attempt to solve the problem of small sample SEM. One of those solutions is found in shrinkage estimation, where a weighted average between the sample variance-covariance matrix (S) and a highly structured shrinkage target (T) is calculated. Different target candidates have already been put forward in the literature (Ledoit, 1995; Ledoit & Wolf, 2003, 2004a, 2004b; Schäfer & Strimmer, 2005), but depending on the study area in which one wishes to apply shrinkage using these targets, not all targets are equally representative of the model one is looking to investigate. The structure of the sample variance covariance matrix in a SEM analysis may deviate substantially from the target structures already proposed. In this poster presentation, we provide a rationale for creating a model-based target specifically for analyzing SEM models as they are typically used in the social and behavioral sciences. Performance of this model-based target is evaluated by means of a simulation study.

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**Poster Session, Wednesday, 16:30-18:00 AND Thursday, 18:15-19:00**

## An Evaluation of Non-Iterative Estimators in Confirmatory Factor Analysis

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***Keywords:*** Confirmatory Factor Analysis, Non-Iterative Estimation

When fitting factor-analytic models, various estimation procedures can be employed. For continuous data, researchers typically resort to Maximum Likelihood (ML), which, except for very special cases, iteratively updates some initial starting values until a predefined convergence criterion is reached. The dominant position of ML is usually ascribed to its optimal limiting properties, such as consistency, asymptotic efficiency, and asymptotic unbiasedness (see, for instance, Bollen, 1989). Perhaps the most noticeable drawback of ML is nonconvergence, which implies that the optimizer fails to land on a stable solution.

Over the course of the previous century, a number of alternative estimation procedures have been proposed, such as the multiple group method (Guttman, 1944; Guttman, 1952; Holzinger, 1944; Thurstone, 1945), FActor Analysis By INstrumental variables (FABIN, Hägglund, 1982), and the non-iterative CFA approach by Bentler (1982). All of these methods are non-iterative in nature, circumventing the issue of non-convergence altogether. In practice, however, their apparent potential remains largely untapped. In this simulation study, we revisit various non-iterative procedures and compare their performance to ML in a wide range of settings. Preliminary results illustrate that non-iterative methods can serve as useful alternatives to ML, especially in settings where the latter estimation procedure tends to fail.

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**Poster Session, Wednesday, 16:30-18:00 AND Thursday, 18:15-19:00**

## The Impact of Multiple Imputation Techniques for Longitudinal Social Network Data

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***Keywords:*** Social Networks, Imputation, Missing Data, SAOM

With improved analysis methods and increasing computational capacity, network regression models are used more frequently in sociological research. Missing data due to unit nonresponse are a much bigger problem using relational network datasets than in analyses using random samples. Hence imputation methods are also gaining in importance. For longitudinal network analyses using Stochastic Actor Oriented Models (SAOM), there is consensus that later waves should be imputed using the internally provided method. The poster presentation compares three different multiple imputation (MI) methods for the first wave of the survey, based on an Exponential Random Graph Model (ERGM), a Bayesian ERGM, and a cross-sectional SAOM ("Stationary SAOM") with the SAOM internal method for all three waves, as well as null imputation and an analysis of a reduced dataset, deleting all missing actors. Comparative analysis with SAOMs and separable temporal ERGMs (STERGM) shows that imputation can improve results and that the effect of the joint tutorial group is overestimated when multiple imputation not used for the first wave. Also, the effects of reciprocity, transitivity, and outdegree activity on student friendships and acquaintances are biased without imputation. The results show little difference between MIs for the specific application in the context of the student network, but show that the use of MI from the first wave onwards can improve the analysis quality significantly compared to a null imputation or deletion of all missing actors. The paper aims to give an application example using real world data containing missings, which research on imputation methods for network data has lacked so far.

**Thursday, 9:30-10:30, Keynote: Craig Enders.** Chair: Kristian Kleinke, “Plenarsaal”, Room 222

## Longitudinal Modeling and Missing Data Handling In Blimp

Craig Enders

*Chair of Quantitative Psychology in the Department*

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The major feature that distinguishes Blimp from other latent variable modeling software packages is that it does not work directly with the multivariate distribution of the analysis variables. Rather, complex multivariate models are represented as sequence of simpler univariate equations. The advantage of this specification is that the individual regression equations can feature mixtures of categorical and normal variables, continuous variables with skewed distributions, interactive or nonlinear terms with latent or manifest variables, and other complex constructions that are difficult to model appropriately with conventional estimation and missing data handling schemes. The talk will introduce attendees to factored regression specifications for longitudinal models and will show how this powerful specification strategy applies to longitudinal models with missing data. The talk will address complexities such as mixed response types, nonlinear and interactive effects, and models for missing not at random processes.

**Thursday, 11:00-12:30, Session C-1: Multiple Imputation with Longitudinal Data I .** Chair: Simon Grund, "Plenarsaal", Room 222

## Multiple imputation of missing data in longitudinal analyses with many variables

Simon Grund[1)], Oliver Lüdtke[2,3)] & Alexander Robitzsch[2,3)]

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***Keywords:*** missing data, multiple imputation, longitudinal data, many variables

Longitudinal data are characterized by a clustered structure, in which observations from multiple time points are nested within participants. In practice, longitudinal data are often incomplete, for example, when participants drop out of the study or fail to provide responses to certain questions or at certain time points. In the statistical literature, multiple imputation (MI) has been shown to provide an effective treatment of missing values in clustered data. However, one crucial requirement of MI is that the imputation model fits the data structure and the intended analyses. In longitudinal data, fulfilling this requirement can be particularly challenging, because the data often contain a large number of variables (e.g., multiple constructs measured at multiple time points) that can exhibit complex patterns of dependency.

In the present talk, we consider different strategies for conducting MI in longitudinal data with many variables and time points. To this end, we first provide an overview of the different strategies, which differ in their representation of the data and their specification of the imputation model. Then, we present the results of a simulation study, in which we evaluated the performance of the different strategies in longitudinal data with fixed measurement occasions and with different complexity and number of variables. Finally, and based on these findings, we discuss the strengths and weaknesses of each strategy and provide recommendations for practice.

**Thursday, 11:00-12:30, Session C-1: Multiple Imputation with Longitudinal Data I .** Chair: Simon Grund, “Plenarsaal”, Room 222

## Robust multiple imputation based on quantile forests

Kristian Kleinke[1)] & Markus Fritsch[2)]

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[2)]*University of Passau*

***Keywords:*** multiple imputation, random forest, quantile forests, quantile regression

Random Forest (RF) is a machine learning method for classification and regression problems that can be enumerated among the ensemble methods - i.e. the classification decision / prediction is based on an ensemble (forest) of relatively independent statistical models (trees), and among the recursive partitioning methods (the training data are split into several classes so that observational units within one class (leafs) are very ‘similar’ to each other, and ‘different’ from observational units of other classes). In the context of missing data imputation, k bootstrap samples are generated from the remaining observed data, and one tree is grown from each bootstrap sample, using a small group of input variables for finding the best split at each node. Predictions are then made for the incomplete observations regarding which leaf they belong to. Finally, one observation is selected randomly from the observed donors of the matched leafs. This process is repeated M-1 times to obtain the M multiple imputations. Imputation by RF is particularly attractive for large datasets, since no imputation model and auxiliary variables need to be specified, and no functional from needs to be specified, since the underlying functional from is approximated in a data-driven fashion. However, little is yet known about the robustness of RF based imputation. The purpose of the present paper is to elucidate to what extent RF-based multiple imputation is robust, and if imputation based on quantile forests (which focus on the conditional median or other quantiles of interest rather than the mean) might work `better', if the data are skewed and heteroscedastic.

**Thursday, 11:00-12:30, Session C-1: Multiple Imputation with Longitudinal Data I .** Chair: Simon Grund, “Plenarsaal”, Room 222

## Multiple imputation of incomplete panel data based on a piecewise growth curve model

Kristian Kleinke[1)] & Jost Reinecke[2)]

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[2)]*Bielefeld University*

***Keywords:*** missing data, multiple imputation, zero-inflation, piecewise growth curve models

Missing data are a nuisance. Complex panel data can be affected by various ‘sources’ of nonresponse including missingness in the target variables, in predictors at level-1, level-2, or higher hierarchical levels, or even missingness in the cluster identifiers. Depending on the type and pattern of missing data, unobserved information poses a threat to the validity of statistical inferences. Modern imputation approaches try to recreate the sample in a way as if ideally no information had gone missing. To this end, the model that is used to create the imputations usually needs to reflect the assumed (and typically unknown) true data generating process, and if necessary, the mechanism that created the missing data patterns, well. If the imputation model is somehow misspecified, bias is to be expected. We focus on complex (nonlinear) relationships of the target variable over time. The purpose of this paper is to elucidate how the choice of the imputation method and model affects substantive model results. We present results of a Monte Carlo Simulation based on empirical data from 12 waves of the Crime in the modern City (CrimoC) study (www.crimoc.org), focussing on the development of juvenile delinquency. The data show the typical age-crame-relationship with an increase in delinquent activities early on in adolescence and a decrease later on. Data were imputed based on a piecewise growth curve model, and based on proxy methods with either a close fit (a growth curve model with a linear and quadratic time trend), or based on relatively robust allround methods such as semi-parametric predictive mean matching. Substantive model results will be discussed in terms of bias in point estimates and standard errors regarding the respective substantive model of interest, regarding ease of use and, and in terms of computing time.

**Thursday, 11:00-12:30, Session E-2: Continuous-Time Modeling II .** Chair: Manuel Voelkle, "Long Table", Room 231 M

## Some Remarks about the History and Philosophical Background of Continuous Time Modeling in Social Science

Johan H.L. Oud

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First social science methodology just after World War Two is characterized, stressing the strongly cross-sectional orientation and divide between psychology and sociology. Next the impact of Jöreskog is described who by SEM not only combined popular models in psychology and sociology, but gave by means of LISREL also a feasible ML estimation procedure for SEM. The first nonstochastic steps in the introduction of continuous time modeling by Simon, Coleman and Blalock are discussed, the stochastic linear time-invariant state space model is presented as well as the exact discrete model (EDM) and the efforts to estimate the model by means of SEM and SSM in the multi-subject case. Associated philosophical issues circling around simultaneity get attention in addition to more recent developments in continuous time modeling in social science. A final philosophical issue is the significance of the quantum mechanical conception of reality for continuous time modeling.

**Thursday, 11:00-12:30, Session E-2: Continuous-Time Modeling II .** Chair: Manuel Voelkle, “Long Table”, Room 231 M

## A moderator variable approach to control for cohort differences in accelerated longitudinal designs

Pablo F. Cáncer, Emilio Ferrer & Eduardo Estrada

***Keywords:*** accelerated longitudinal designs, cohort differences, state-space models, latent change score models, continuous time models

Purpose. Accelerated longitudinal designs (ALD) allow studying developmental processes usually spanning many years in a much shorter time frame. The key assumption of ALDs is that individuals from different cohorts (i.e., born in different years) belong to the same population, and thus the populational trajectory can be described by a shared set of parameters. However, participants born in different years may have been exposed to different contextual factors, leading to differences in their developmental patterns. According to previous research, failing to account for such differences will result in unreliable estimates. As a solution to this problem, we propose an extension of the latent change score model in continuous time that captures cohort effects in the context of ALDs. In particular, we focus on cohort differences in the self-feedback parameter.

Method. Through a Monte Carlo study, we examined the performance of the proposed model under different conditions of sample size, sampling schedule, and size of cohort differences.

Results. The proposed model adequately detects and controls for cohort differences in ALDs, regardless of the size of such differences. When the appropriate sampling schedule is selected, the performance of the model is excellent even with sample sizes of 125 individuals.

Discussion. We discuss the most relevant findings, elaborate on the strengths and limitations of our approach, and provide recommendations about the design of longitudinal studies. We encourage researchers to use the proposed model when they expect differences across cohorts in their patterns of change.

**Thursday, 11:00-12:30, Session E-2: Continuous-Time Modeling II .** Chair: Manuel Voelkle, "Long Table", Room 231 M

## Continuous-Discrete Filtering using the Duncan-Mortensen-Zakai (DMZ) Equation: Smooth Likelihood Surface


Hermann Singer

*FernUniversität Hagen, Germany*



The continuous time state space model consists of a dynamical equation for the unobserved state (stochastic differential equation SDE) and a measurement equation, also described by an SDE. We attempt to estimate the unknown parameters (drift, diffusion, factor loadings, measurement error etc.) by maximum likelihood.

The unnormalized filter density (state probability density at present time, given the measurements up to this time), fulfils a stochastic partial differential equation, the DMZ equation. It is a Fokker-Planck equation with additional potential term containing the measurements. The likelihood function is determined by integration over the unnormalized filter density. In the proposed algorithm, numerical quadrature will be utilized. For continuous-discrete filtering, only integrals at discrete times of measurement must be considered.

As it is well known, standard particle filter algorithms suffer from the problem (due to resampling), that the estimated likelihood is not a smooth function of the model parameters. One can improve the resampling procedure (Malik and Pitt, 2011), but this approach is involved in the multivariate case.

The DMZ equation is transformed to a backward Kolmogorov equation which is solved by Monte Carlo integration using importance sampling (similar to option pricing in finance). Since no resampling is required, we obtain a smooth likelihood surface. A drawback is the possibly large number of grid points where the unnormalized filter density must be evaluated. The results are compared with approximations based on a matrix representation of the Fokker-Planck operator and with particle filtering.

**Thursday, 13:30-14:30, Keynote: Christian Geiser.** Chair: Axel Mayer, “Plenarsaal”, Room 222

## Latent state-trait analysis: State of the art and future directions

Christian Geiser

*Co-founder and director of QuantFish LLC*

Latent state-trait (LST) models were developed to account for situation-specific aspects in the measurement of social science constructs. LST models have since been refined and extended in various ways. In this presentation, I give an overview of the history and recent developments and point out areas in need of further development.

**Thursday, 15:00-16:30, Session D-1: Causal Inference and Causal Mediation .** Chair: Daniel Seddig, “Plenarsaal”, Room 222

## Causal Effect Estimation in Large-Scale Assessment Data: Using a Multi-group Structural Equation Model with Categorial Indicators in EffectLiteR

Marie-Ann Sengewald[1,2] & Axel Mayer[3]

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[2] *Otto Friedrich University Bamberg, Germany*

[3] *Bielefeld University, Germany*

Well-constructed achievement tests are a special strength of educational large-scale assessments (LSAs) and the students’ proficiencies are frequently of main interest in subsequent analysis - like for the comparison of respondent groups. In these non-randomized comparisons, the estimation of covariate adjusted group differences is common practice. Yet, often fallible test scores, instead of the latent proficiencies itself, are used as a manifest outcome or covariate. The EffectLiteR package allows for directly including latent variables in a multi-group structural equation model for causal effect analysis and we recently provided an extension that facilitates latent variable models with categorical indicators. Using an example from the National Education Panel Study (NEPS), we show the implementation and benefit of this approach. Specifically, we investigate the effect of tutoring in mathematics on a subsequent math ability measure, while controlling for the previous math ability and additional covariates of the participants. The application is well-suited for illustrating theoretical conditions under which measurement error in test scores biases treatment effects and provides item-level data, based on which different strategies for modeling a latent outcome or latent covariates can be compared (i.e., a direct integration of latent variable models, fallible score estimates or plausible values from latent variable models). The implementation of the modeling approaches and the practical benefit of using latent variables in comparison to proficiency scores is of special interest in the application and discussion.

**Thursday, 15:00-16:30, Session D-1: Causal Inference and Causal Mediation .** Chair: Daniel Seddig, “Plenarsaal”, Room 222

## Stochastic covariates-based treatment effects from non-linear regression models

Christoph Kiefer

*Bielefeld University*

***Keywords:*** causal inference, stochastic covariates, non-linear regression models
Category: SEM and Causality

Recent developments in statistical inference on causal effects have laid a stronger focus on adequately accounting for the sampling processes of the social sciences. Traditional models in the social sciences as well as effect estimation procedures often assume that properties of a sample as, for instance, the overall or groups' size or even observed values of a covariate, would be predetermined by the researcher and only the outcome variable does vary across sample. However, the opposite is true in many applied scenarios where random sampling of persons is conducted and the observations and observed properties of the sample are 'stochastic'. Many researchers have shown that neglecting stochastic group sizes or stochastic covariates can have an adverse impact on the validity of statistical inferences on causal effects, typically leading to deflated standard errors and increased Type 1 error rates. In this talk, we give a brief overview of our recent studies and findings on the role of stochastic covariates for effect estimation in non-linear regression models (i.e., Poisson and logistic regression models). We illustrate why controlling for stochastic covariates is especially important if a treatment variable has very different effects for different persons and discuss why this also applies in settings with bounded effect ranges (e.g., binary outcomes). In addition, we compare two approaches of accounting for stochastic covariates in non-linear regression models, finding that both outperform statistical inferences based on the fixed-covariate assumption if covariate' values were indeed randomly sampled. Thus, accounting for stochastic covariates is discussed as an important aspect of statistical inference in treatment effect estimation, especially in light of heterogeneous effects and/or random, non-predetermined sampling processes in general.

**Thursday, 15:00-16:30, Session D-1: Causal Inference and Causal Mediation .** Chair: Daniel Seddig, “Plenarsaal”, Room 222

## A simulation study of different approaches to mediation analysis in presence of unobserved heterogeneity and reverse causality

Dominik Becker

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***Keywords:*** analysis; reverse causality; unobserved heterogeneity; simulation study; (causal panel modeling)

Whether an observed association between two social constructs is due to a causal effect is a fundamental methodological question in the social sciences. The additional question of how a causal effect is brought about is usually answered by mediation models investigating whether a significant parameter estimate from some type of regression of Y on X persists once mediator M is controlled for.

Concerning the analysis of panel data, unobserved heterogeneity and reverse causality are wellknown challenges that have yet been less frequently considered within statistical approaches to mediation analyses. This contribution compares the average bias of different approaches to mediation analysis – i.e., simple mediation within pooled OLS regressions (POLS), fixed-effects (FE) regressions, generalized-method-of-moments (GMM) regressions, causal mediation analysis without (CM) and with fixed effects (CMFE), and fixed-effects cross-lagged panel models (FECLPMs) – in presence of unobserved heterogeneity and reverse causality. To do so, I conduct simulation analyses of generated panel data within which intercorrelations between predictor, mediator and outcome are varied across different scenarios of causal order. Special emphasis will be laid on the sensitivity of each approach in case of an unobserved confounder affecting the mediation effect.

Preliminary results suggest that POLS estimates are generally upwardly biased, FE and CMFE estimates by trend downwardly biased, while estimates of CM models (without FEs) can be biased in both directions. In contrast, coefficients and confidence intervals estimated by both GMM regressions and FE-CLPMs are most accurate – particularly if the estimated structure of lags meets the consecutive order implied by the data-generating process. Unlike GMMs, FECLPMs are hardly sensitive to whether the first lag of the outcome variable is included as an additional predictor. Next steps involve to explore the average bias of each approach in estimating the mediation effect when an unobserved confounder affects the mediator with variable simulated regression weights.

**Thursday, 15:00-16:30, Session D-1: Causal Inference and Causal Mediation .** Chair: Daniel Seddig, “Plenarsaal”, Room 222

## The Parametric g-Formula for Latent Markov Models

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***Keywords:*** Causal Inference, Parametric g-Formula, Post-Treatment Confounding, Latent Markov Model, Unobserved Outcomes

Post-treatment confounding poses a major challenge for causal inference on longitudinal data. When data is collected within an observational study design, there will be a self-selection process into the treatment groups and the causal effect of a treatment on an outcome of interest will be confounded. This problem intensifies with repeatedly measured outcomes when individuals are allowed to switch between treatment groups. E.g., a treatment might not have the expected effect on the outcome for some individuals and treatment might therefore be adjusted at follow-up. It is also possible that treatment affects some time-varying confounders which then affect treatment allocation at follow-up. If this happens, the average treatment effect will be confounded. To solve this problem of post-treatment confounding, the parametric g-formula has been proposed. In the social sciences, however, this framework needs to be extended as we are often confronted with outcomes that are not directly observable but are measured through indicators, i.e., are latent. For longitudinal data, latent Markov models are a common choice for modelling such outcomes. In this talk, I will present an extension of the parametric g-formula for unobserved outcomes. In a stepwise approach, we first estimate the measurement part of the latent Markov model. With the measurement model fixed, we then combine the estimation of the Markov-chain with the parametric g-formula to account for time-varying confounding.

**Thursday, 15:00-16:30, Session C-2: Multiple Imputation with Longitudinal Data II .** Chair: Kristian Kleinke, "Long Table", Room 231 M

## Imputation of missing longitudinal data using the broken stick model

Stef van Buuren

*University of Utrecht*

*TNO, Netherlands Organisation for Applied Scientific Research*

There are two general strategies for the multiple imputation of missing longitudinal data. If the data are collected at similar times, we can organise the data as a broad matrix and impute under the assumption of independence of rows. This approach is simple and flexible but inefficient if there are many time points or if time points differ between observations. The second strategy involves organising the data with time in the rows and imputing it by a mixed model using time as a covariate. This approach has become possible thanks to recent advances in methodology and software but it requires deep methodological and technical expertise. In this presentation, I explore a third strategy, the broken stick model, which combines the simplicity of the broad approach with the technical advantages of the mixed model. The broken stick model transforms data collected at irregular time points to a raster of regular time points. This raster is the same for all observations, so effectively, we replace the irregular data with a simpler set of repeated measures. I will illustrate the essential workings of the method and explain how multiple imputation accommodates for the inherent loss of information induced by the transform.

**Thursday, 15:00-16:30, Session C-2: Multiple Imputation with Longitudinal Data II .** Chair: Kristian Kleinke, “Long Table”, Room 231 M

## The Performance of Multiple Imputation in Social Surveys with Missing Data from Planned Missingness and Item Nonresponse

Julian Axenfeld

*University of Mannheim*

***Keywords:*** imputation, planned missingness, split questionnaire design

Designs using planned missingness, such as the split questionnaire design, are becoming more and more important in social survey research. To ensure an acceptable questionnaire length, these approaches typically entail large amounts of planned missing data, which can be imputed after data collection. However, social surveys typically also include other types of missingness such as item nonresponse by survey participants, which need to be imputed as well. This entails a complex imputation task with amounts of missing data larger than initially planned and a potentially non-random, heterogeneous mechanism. Since previous research regarding the imputation of planned missingness did not take additional nonresponse into account, it remains to be studied whether accurate multiple-imputation estimates can be obtained in practice with planned missingness and item nonresponse.

To deal with this research gap, in this paper we apply a Monte Carlo simulation study using real social survey data from the German Internet Panel. In this study, we simulate missing data based on item nonresponse with different mechanisms and proportions of item nonresponse as well as different proportions of planned missing data. We find that item nonresponse can jeopardize the quality of estimates after multiple imputation especially when the total amount of missing data from both sources is high or when there is a considerable proportion of item nonresponse that is missing not at random. Therefore, from an imputation perspective, survey designers should incorporate their expectations about item nonresponse on each variable when designing surveys with planned missing data.

**Thursday, 16:45-18:15, Session H-1: Measurement Invariance and IRT-Modeling .** Chair: Heinz Leitgöb, “Plenarsaal”, Room 222

## The decomposition of true change and response shifts in latent constructs across time

Heinz Leitgöb[1,2] & Daniel Seddig[3]

*[1]University of Leipzig, Germany*
*[2]University of Frankfurt, Germany*
*[3]University of Cologne, Germany*

Many phenomena of interest in the social sciences are not directly observable. Rather, they are conceptualized as latent constructs measured via multiple manifest indicators. Measurement models, such as CFA or IRT models, are utilized to formalize the link between the latent and manifest worlds.

In longitudinal panel studies, valid inferences about the temporal development of a latent construct require that the parameters of the measurement models (e.g., intercepts, factor loadings) are invariant across time. If measurement invariance is not given, cross-time changes in the means and variances of the latent variables are not adequately interpretable because the changes do not only reflect the temporal development of the latent construct (true change) but also systematic changes in the response behavior of the panel population (response shifts).

Nevertheless, it is still possible to learn from the data in such situations. Oort (2005) proposed a threefold linear decomposition of the differences in manifest indicator means into (i) two response shift components and (ii) a true change component, based on the CFA panel data. We propose an extension of the approach, which contains a different identification strategy, estimators for the standard errors of the decomposition components, and possibilities for the graphical visualization of the results.

We demonstrate an empirical application of the extended decomposition procedure using panel data from the CrimoC project.

***Reference***

Oort, F. (2005). Using structural equation modeling to detect response shifts and true change. Quality of Life Research, 14, 587–598.

**Thursday, 16:45-18:15, Session H-1: Measurement Invariance and IRT-Modeling .** Chair: Heinz Leitgöb, "Plenarsaal", Room 222

## Assessing Individual Change with Item Response Models

Rainer W. Alexandrowicz[1)] & Ferdinand Keller[2)]

[1)]*Universität Klagenfurt*

[2)]*Universitätsklinikum Ulm, Germany*

The tradition of statistical assessment of individual change trades back at least to the 90ies of the last century. These "classical" approaches basically build on the standard error of measurement (S.E.M), which, in turn, is based on an estimation of reliability. Therefore, a simple "score difference divided by S.E.M."-index has been termed "Reliable Change Index", RCI. With the uprise of Item Response Theory models (IRT), the same principle has been adopted.
However, the multitude of available models here allows for various ways to calculate an RCIIRT. Interestingly, these variants have not been discussed in great detail, although they will likely deliver different results.
The current study explores the effect of different IRT modelling strategies have on the results in a large simulation study and a real-data application of a clinical study involving the BDI-II. The simulation study involves separate, multi-group, and multi-dimensional calibration. From the results, the third variant turns out optimal, because it takes into account the correlation of the repeated measurement. Similarly, the real-data application also revealed large differences of the various techniques.

**Thursday, 16:45-18:15, Session H-1: Measurement Invariance and IRT-Modeling .** Chair: Heinz Leitgöb, “Plenarsaal”, Room 222

## Alignment of longitudinal models

Tihomir Asparouhov

*University of California*

We describe an adaptation of the multiple group alignment methodology to longitudinal models. Latent variables are measured repeatedly across time with possible measurement non-invariance. The alignment method allows us to estimate time specific latent variable distribution in addition to time specific measurement models. We describe a connection between the alignment method, the penalized maximum-likelihood method and the Bayesian SEM method. This allows us to utilize the alignment methodology in a variety of longitudinal models such as growth models and RI-CLPM models.

**Thursday, 16:45-18:15, Session G-1: Growth Curve and Multi-Level Modeling I.** Chair: Thomas Blank, “Long Table”, Room 231 M

## Recent advances in accelerated longitudinal designs to study psychological development.

Eduardo Estrada

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***Keywords:*** accelerated longitudinal design; structural equation modeling; continuous time modeling; cognitive development

Studying the long-term course of psychological processes is a challenging endeavor. Accelerated longitudinal designs (ALD) allow capturing such periods in a much shorter time framework. In ALDs, participants from different cohorts are measured repeatedly but the measures provided by each participant cover only a fraction of the time range of the study. It is then assumed that the common trajectory can be studied by aggregating the information provided by the different converging cohorts.

In this communication, I present ALDs and discuss their effectiveness for longitudinal research. I present the main results of a set of recent studies, which support the application of ALDs in a broad set of conditions (Estrada & Ferrer, 2019; Estrada, Hamagami, & Ferrer, 2020; Estrada, Bunge, & Ferrer, 2021). I provide several recommendations on how to design such studies, and briefly introduce several statistical innovations to characterize the developmental trajectories of interest.

**Thursday, 16:45-18:15, Session G-1: Growth Curve and Multi-Level Modeling I.** Chair: Thomas Blank, "Long Table", Room 231 M

## Specifying composites in growth curve analysis

Xi Yu,[1)] Florian Schubert[1)] & Jörg Henseler[1,2)]

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2) *Nova Information Management School, Universidade Nova de Lisboa, Portugal*

***Keywords:*** Composites, emergent variables, growth curve analysis, structural equation modeling, longitudinal data analysis

To study composites in growth curve models, researchers typically follow the composite score approach, which is a two-step approach. In the first step, composites are created outside the model and subsequently, in the second step these composites are treated as observed variables in the growth curve model. Due to its two-step nature, the composite score approach has various drawbacks such as weights are no model parameters and the overall model fit assessment ignores the formation of the composites. To address these drawbacks, we present a new approach which allows for specifying composites in growth curve models in a single step. In doing so, we combine on the recently proposed Henseler–Ogasawara specification with the growth curve model. Consequently, researchers can estimate growth curve models containing composites in a single step. To illustrate our approach, we use an empirical example. Finally, we provide avenues for future research.

**Thursday, 16:45-18:15, Session G-1: Growth Curve and Multi-Level Modeling I.** Chair: Thomas Blank, "Long Table", Room 231 M

## Examining Nonlinear Science Achievement Growth Using Early Childhood Longitudinal Study-Kindergarten: 2011

Tingting Reid

*University of Hildesheim*

Much of the extant literature in achievement studies employs linear models, which assume that students' growth occurs at a constant rate over an extended period. Although other growth modeling approaches are often used to capture nonlinear growth, such as higher order polynomials (e.g., quadratic, cubic) and mixtures with different growth trajectories, interpretation of such models is often intractable substantively (e.g., Kirk, 2013). Researchers have underscored the need in formulating nonlinear models that can more fully examine the total change experienced, the rate of change as well as the timing of peak change that are more compatible with the learning curves in educational theories (Blozis & Harring, 2016; Preacher & Hancock, 2015). The present study leverages a national representative sample consisting of 18,174 children from 1,310 elementary schools in the United States where data were collected biannually during kindergarten and fifth grade. The final data set consisted of 2,916 students with appropriate strata, PSU, and longitudinal weights applied to optimally handle the nonresponse missing data. Compared to the earlier ECLS-K:1998 study, ECLS-K:2011 is advantageous in aptly assessing the rapid developmental changes occurring between ages 5 and 7 years, commonly known as the 5-to-7-year shift (Sameroff & Haith, 1996). Science achievement scores were vertically linked item-response- theory scaled scores that allows us to make clear inferences about the shape of growth across time. In sum, this study aims to (1) apply a statistical technique that has been relatively underemployed—Gompertz growth modeling in the domain of science learning from kindergarten through fifth grade; and (2) examine the dynamic relations between science literacy instruction and achievement growth by adding time-varying predictors. Our subsequent analyses will include a wider range of covariates including school level contextual variables to better understand the micro- and meso-factors impacting children's science achievement growth.

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**Friday, 9:30-10:30, Keynote: Fan Y. Wallentin.** Chair: Peter Schmidt, “Plenarsaal”, Room 222

## A Marginal Maximum Likelihood Approach for Extended Quadratic Structural Equation Modeling with Ordinal Data

Fan Y. Wallentin

*Professor of Statistics at Uppsala University, Sweden*

The literature on non-linear structural equation modeling is plentiful. Despite this, few studies consider interactions between exogenous and endogenous latent variables. Further, it is well known that treating ordinal data as continuous produces bias, a problem that is enhanced when non-linear relationships between latent variables are incorporated. A marginal maximum likelihood-based approach is proposed to fit a non-linear structural equation model, including interactions between exogenous and endogenous latent variables in the presence of ordinal data. In this approach, the exact gradient of the approximated observed log-likelihood is calculated to attain the approximated maximum likelihood estimator. A simulation study shows that the proposed method provides estimates with low bias and accurate coverage probabilities.

**Friday, 11:00-12:00, Session B-1: Non-linear Structural Equation Modeling.** Chair: Yves Rosseel, "Plenarsaal", Room 222

# Latent Moderation with many predictors and simultaneous equation systems: Comparison and application of Latent Moderated Systems (LMS), Product Indicator (PI) approaches and Structural after measurement approach (SAM) using the example of an empirical study.

Yannick Diehl[1] & Peter Schmidt[2]

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***Keywords:*** Moderation Effects in Latent Variables

Almost all applications of latent moderation introduce only a single moderation effect into their models. However, in many frequently used theories such as the Reasoned Action Approach/Theory of Planned Behavior (Fishbein/Aizen 2010), many moderation effects are postulated, including those between exogenous and endogenous constructs. In this paper we want to compare three approaches: (1) Latent Moderated Systems (Klein & Moosbrugger, 2000), (2) Product Indicator approaches specifically double-mean-centering approach (Lin et al. 2010) and orthogonalized approach (Little, Bovaird & Widaman 2006) and (3) Structural after measurement approach. The first two methods estimate the free parameters of the model simultaneously. The third approach builds on the (local) structural-after measurement approach that was recently proposed by Rosseel & Loh (in press). One estimates the parameters of the measurement part of the model in stage one. The measurement parameters, together with the sample statistics, are then used to construct an estimate of the variance-covariance matrix of the latent variables: Var(η). This variance-covariance matrix is used in the second stage, where one estimates the relationships among the latent variables including quadratic and interaction terms of the structural part of the model (Rosseel, Y. & Loh, W.W., in press). We apply these three approaches to a study of environmental behavior with a sample size of N = 404 and four moderation effects simultaneously including one between an exogenous and an endogenous latent variable. The comparison includes the computation time, whether the model could be estimated at all, point estimates, standard errors and the fit of the model.

**Friday, 11:00-12:00, Session B-1: Non-linear Structural Equation Modeling.** Chair: Yves Rosseel, "Plenarsaal", Room 222

## Estimating Power in Moderated Mediation Models and Endogenous Moderation Model: The *pwrModMed* R-package

Julien P. Irmer, Andreas G. Klein, and Karin Schermelleh-Engel

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***Keywords:*** moderation, mediation, interaction, LMS, factor scores, R

Moderated-mediation models as well as endogenous moderation models are increasingly used because research questions are becoming more complex. With the increase in complexity, many parameters need to be estimated. To reduce the number of parameters, many researchers still rely on moderated regression or path analysis using scale means and product variables to examine their research questions, thereby ignoring that data were not collected without measurement error. Many methods have been developed, which also model measurement error, but which rely on rather strong distributional assumptions and require many parameters to describe the data. To plan their research designs, researchers are often interested in power analyses. Simulation based power analyses have already been implemented for regression-type analyses, but an extension to methods modeling measurement errors is still lacking. Therefore, we examined complex latent moderator and mediator models and conducted a power analysis for scale regression analyses compared to more sophisticated but easy-to-use methods (latent moderated structural equations, LMS, Klein & Moosburgger, 2000, simplified factor score approach, Ng & Chan, 2020) in a simulation study using a logistic regression model to predict power for large numbers of different sample sizes and effect sizes. The results of the power analyses are provided and the problem concerning the tradeoff between method complexity and performance is discussed. We aim at providing a user-friendly R package that can be used to estimate the power of complex models with moderator and moderated mediation effects in latent variable modeling.

**Friday, 11:00-12:00, Session B-1: Non-linear Structural Equation Modeling.** Chair: Yves Rosseel, "Plenarsaal", Room 222

## Cause for Concern: Omitted Cross-Loadings in Measurement Models of Nonlinear Structural Equation Models

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***Keywords:*** nonlinear structural equation modeling, cross-loadings, model misspecification, interaction effect, quadratic effect, Monte Carlo study

Nonlinear structural equation modeling (SEM) generally assumes that all indicators of the measurement models are unidimensional, an assumption that is often violated in empirical research. Recent research on linear SEM has already shown that omitting positive crossloadings results in biased parameter estimates, with some paths being overestimated and other paths being underestimated. For nonlinear SEM, the consequences of omitting cross-loadings have not yet been systematically investigated. Because of the high complexity of these models, due to higher order terms in the model that are generally correlated, the effects of omitted cross-loadings are expected to be more severe than for linear SEM.

In a Monte Carlo study, we examined the patterns of parameter bias due to omitted crossloadings in measurement models of three nonlinear SEMs with increasing numbers of nonlinear effects (moderator effect, moderator and quadratic effect, moderator and two quadratic effects) by varying the sign and size of cross-loadings, nonlinear effects, and predictor correlation as well as sample size. The results demonstrate the detrimental effects of omitted cross-loadings with different patterns of overestimation or underestimation of all structural parameters. The results also show that under certain conditions, omitted crossloadings altered the nature of the relationships between predictor and criterion variables. A tentative explanation for the different patterns of bias is provided.

**Friday, 11:00-12:00, Session D-2: (Causal)Panel Modeling and Applications.** Chair: Christina Beckord, “Long Table”, Room 231 M

## Does loneliness contribute to psychological distress? A longitudinal analysis using data from the Understanding Society Panel Study 2017-2021.

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***Keywords:*** Causal Panel Modeling, Fixed Effects Models, Understanding Society, Loneliness, Mental Health

*Introduction:* Loneliness is widely regarded as a major risk factor for psychiatric disorders. Although previous research has demonstrated a strong link between loneliness and mental illness, the causal nature of this association is still critically debated. While socio-cognitive models assume that loneliness contributes to psychiatric disorders through negative cognitive biases that set off a series of affective, behavioral, and biological processes (e.g., HPA axis dysregulation), other explanations emphasize the role of selection and suggest that symptoms of psychiatric disorders and/or associated vulnerabilities (e.g., genetic factors, early traumatic experiences) lead to impaired social functioning and social stigma that increase feelings of loneliness. This study seeks to disentangle the two perspectives by analyzing whether loneliness is still associated with psychological distress when accounting for selection.

*Data and Methods:* The analytic sample was drawn from the Understanding Society Panel 2017-2021. Psychological distress was assessed using the GHQ-12, and loneliness was measured using the 3-item UCLA Loneliness Scale and a single item measure. The study applies fixed effects models with individual slopes (FEIS) to account for the possibility that individuals with less favorable distress trajectories self-select into loneliness.

*Results:* Compared to previous research, the association between loneliness and psychological distress was significantly reduced when accounting for selection on distress trajectories, but its magnitude remained substantial. The differences amounted to approximately .5 to 1.5 within-individual standard deviations of the outcome, indicating moderate to large effect sizes. The results were highly consistent for both genders and across measures of loneliness.

*Discussion:* The results provide strong evidence that loneliness contributes to psychological distress, but also show that the role of selection has been understudied in previous research. Intervention strategies should focus more on mitigating the negative social outcomes of psychiatric disorders and associated vulnerabilities to break the vicious cycle of loneliness and mental illness.

**Friday, 11:00-12:00, Session D-2: (Causal)Panel Modeling and Applications.** Chair: Christina Beckord, “Long Table”, Room 231 M

## Rehabilitating the Lagged Dependent Variable with Structural Equation Modeling

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***Keywords***: causal analysis, panel analysis, cross-lagged panel models, autoregression, collider bias

There is a long history of including the lagged dependent variable in panel models, especially in the structural equation modeling framework. These include, but are not limited to, cross-lagged panel models, for example.

However, it is often argued that this practice is ill-advised. Namely, in the presence of time-invariant unobserved heterogeneity, the inclusion of the lagged dependent variable is said to open up unintended back-door paths and bias the estimates of the causal variable. Much existing literature therefore recommends avoiding lagged dependent variable models.

We show that panel analysis in the structural equation modeling framework is generally not affected by this issue. Including the lagged dependent variable has the benefit of closing back-door paths due to unobserved time-varying confounders. The existence of time-invariant unobserved confounders is unproblematic.

We demonstrate this using simulated data and argue that the broad use of cross-lagged panel models is legitimate and these models can provide benefits compared to models that do not include the lagged dependent variable.

**Friday, 11:00-12:00, Session D-2: (Causal)Panel Modeling and Applications.** Chair: Christina Beckord, “Long Table”, Room 231 M

## Examining Parameter Differences in Latent State-Trait Models: Modeling Loneliness During COVID-19 Lockdowns Using a Bayesian Moderated Nonlinear Latent State-Trait Approach

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***Keywords:*** Latent State-Trait-Models; Bayesian Structural Equation Models; Moderated Factor Analysis

Latent state-trait (LST) models are widely used for analyzing complex longitudinal data that may exhibit both trait change and autoregressive (carry-over) effects. Oeltjen and colleagues (2022) recently proposed a moderated nonlinear LST (MNLST) approach that allows researchers to include both time-varying and time-invariant variables to explain differences in additive and multiplicative trait change parameters as well as state residual variances and autoregressive effects. The present talk aims at (1) illustrating the MNLST approach using data of a study examining loneliness across six measurement occasions during COVID-19 lockdown periods in Germany; (2) presenting model set-up in a Bayesian framework using the probabilistic programming language Stan; and (3) illustrating Bayesian model evaluation using posterior predictive checks and leave-one-out cross-validation.

**Friday, 11:00-12:00, Session D-2: (Causal)Panel Modeling and Applications.** Chair: Christina Beckord, “Long Table”, Room 231 M

## Whose generalized trust is shattered by criminal victimization? Using various methods to study heterogenous causal effects

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***Keywords:*** heterogenous causal effects; criminal victimization; generalized trust

A growing body of research shows that life experiences can change adults’ generalized trust, that is, their beliefs that people are generally trustworthy. Yet, the impact of criminal victimization – an experience with particular potential to shatter trustworthy beliefs – has rarely been adequately studied. Most extant research relied on cross-sectional data and findings thus suffer from low internal validity. Moreover, studies have typically failed to consider that victims might respond differently to victimization and that only some people may lose trust in others. The current work addresses this research gap by studying the question: Whose generalized trust is shattered by criminal victimization? Using data from two-wave panel studies conducted in Cologne and Essen (Germany), various analytical procedures were applied (matching, change score models, machine learning procedures) to estimate causal effects and how these differ across victims. The findings obtained from the various procedures are discussed in terms of their internal validity.

## Integrating complex panel data models into dynamic microsimulations: an application to the analysis of the migrant and gender pay gaps in Germany

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***Keywords:*** Dynamic Panel Models, Growth Curve Modeling, Microsimulation, Life Course Analysis, Wage Inequalities

In this contribution, innovative panel data methods are used to model individual wage trajectories and, subsequently, emerging inequality measures (e.g., pay gaps). The aim is to develop techniques to integrate the principles of these complex panel models into the framework of dynamic microsimulations in order to project potential wage developments in different scenarios.

Individuals' wages develop from a complex interplay of self-acquired and parental resources. Discriminatory processes can influence this development. Moreover, the aggregate extent of discrimination against groups varies over time and can be triggered by sociopolitical changes or dynamics in the population composition. Such processes do not only lead to changing wage developments at the individual level. Indicators of discrimination on the macro-level, such as the adjusted gender and migrant pay gaps, might also develop dynamically.

Therefore, the first step of this contribution is to use panel data to analyze the interplay between endogenous dynamics within life courses, changing societal conditions, and changing population composition. In this way, we can explore under which conditions and to what extent group-specific average wages and consequently pay gaps develop. This can be done with dynamic panel models or growth curve modeling. Recently, approaches have been presented which combine these two types of models, enabling us to model life courses more precisely.

The wage dynamics identified in our empirical analyses are projected into the future using microsimulation modeling techniques based on different scenarios. This approach is necessary as we focus on the relatively young third generation of migrants in Germany, who are of particular theoretical interest, but for whom empirical research is scarce. In this context, we face the methodical challenge of integrating the results of complex panel data models into our microsimulation. We present strategies to meet this objective as well as empirical and simulated results.

**Friday, 13:30-15:00, Session B-2: Non-Linear Structural Equation Modeling and Mode Effects.**
Chair: Peter Schmidt, “Plenarsaal”, Room 222

## A structural-after-measurement (SAM) approach for latent moderation

Yves Rosseel

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***Topic:*** Moderation Effects in Latent Variables

Several methods have been proposed to include quadratic or interaction terms involving latent variables in structural equation models. Some examples are the latent moderated structural equations approach (LMS; Klein & Moosbrugger, 2000), the nonlinear structural equation mixture approach (NSEMM; Kelava & Brandt, 2014), and several variants of the product indicator (PI) approach (Kenny & Judd, 1984; Marsh, Wen, & Hau, 2004). All these methods use a system-wide estimation approach and estimate the free parameters of the model simultaneously. This is in contrast to the 2-stage method of moments estimator (2SMM; Wall & Amemiya, 2003) where factor scores are computed in a first stage, and an errors-in-variable regression approach is used in the second stage. In this presentation, I will describe an alternative approach that is similar in spirit to 2SMM, but where we avoid the explicit calculation of factor scores. The approach builds on the (local) structural-aftermeasurement (SAM) approach that was recently proposed by Rosseel & Loh (in press). Just like 2SMM, we first estimate the parameters of the measurement part of the model in stage one. The measurement parameters, together with the sample statistics, are then used to construct an estimate of the variance-covariance matrix of the latent variables: $\mathrm{Var}(\eta)$. This variance-covariance matrix is used in the second stage, where we estimate the (linear) relationships among the latent variables. It turns out that we can also derive explicit expressions for $\mathrm{Var}(\eta \otimes \eta)$ and $\mathrm{Cov}(\eta, \eta \otimes \eta)$ where $\otimes$ denotes the Kronecker product (Burghgraeve, 2021). This allows for easy inclusion of quadratic and interaction terms in the structural part of the model. Preliminary simulation results indicate that the approach works well, even in the presence of distributional and structural misspecifications.

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**Friday, 13:30-15:00, Session B-2: Non-Linear Structural Equation Modeling and Mode Effects.**
Chair: Peter Schmidt, "Plenarsaal", Room 222

## A small sample correction for factor score regression


Jasper Bogaert, Wen Wei Loh, & Yves Rosseel

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Factor score regression (FSR) is widely used as a convenient alternative to traditional structural equation modeling (SEM) for assessing structural relations between latent variables. But when latent variables are simply replaced by factor scores, biases in the structural parameter estimates often have to be corrected, due to the measurement error in the factor scores. The method of Croon (MOC) is a well known bias correcting technique. However, its standard implementation can render poor quality estimates in small samples. A small sample correction (SSC) has been developed by integrating two different modifications to the standard MOC. We conducted a simulation study to compare the empirical performance of (i) standard SEM, (ii) the standard MOC, (iii) naive FSR, and (iv) the MOC with the proposed SSC. In addition, we assessed the robustness of the performance of the SSC in various models with a different number of predictors and indicators. The results showed that the MOC with the proposed SSC yielded smaller mean squared errors than SEM and the standard MOC in small samples and performed similarly to naive FSR. However, naive FSR yielded more biased estimates than the proposed MOC with SSC, by failing to account for measurement error in the factor scores.

**Friday, 13:30-15:00, Session B-2: Non-Linear Structural Equation Modeling and Mode Effects.**
Chair: Peter Schmidt, “Plenarsaal”, Room 222

## Estimating Mode Effects in Panel Surveys: A Multitrait Multimethod Approach

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***Keywords:*** panel surveys, mode effects, measurement error, multi-trait-multi-method

An increasing number of longitudinal studies worldwide cover societal change over decades. Fieldwork of these panel surveys experienced notable technological advancements and often switched modes of data collection over time. A large body of literature documents that the mode of data collection matters for respondent behavior, however, empirical evidence of mode effects on estimates of reliability and validity is surprisingly scarce. The paper proposes to adapt the experimental Multitrait Multimethod (MTMM) approach to observational data. For this purpose, we use the longitudinal data from the German Socio-Economic Panel (SOEP), an annual panel study started in 1984 with interviewer-administered paper and pencil interviews and nowadays additionally using computer assisted personal interviewing as well as self-administered questionnaires, both mailed and web-based. While mode changes in the SOEP are not randomly assigned to respondents, we augment our approach by propensity score weighting to reduce selection bias in estimates of mode effects. Our analysis suggests moderate but statistically significant differences in reliability and validity estimates between modes of data collection. Generally, method effects are more prevalent in interviewer-administered compared to self-administered survey data.

**Friday, 13:30-15:00, Session G-2: Growth Curve and Multi-Level Modeling II.** Chair: Jost Reinecke, "Long Table ", Room 231 M

## On evaluating the performance of model fit and selection indices for Bayesian piecewise growth modeling: The effect of model misspecification and missing data

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***Keywords:*** Bayesian piecewise growth model, model misspecification, missing data, model fit, model selection

The way social and behavioral phenomena change over time is a central question to latent growth modeling. The piecewise growth model (PGM) is an extension of the latent growth model and analyzes nonlinear change processes consisting of distinct growth phases by introducing knots. The Bayesian framework offers additional advantages to PGMs by estimating complex growth phases and incorporating prior information. Applications of Bayesian PGMs pose three important issues. First, researchers should consider knot placement to determine specific time points in which growth patterns change. This issue should be addressed through the use of model fit and selection indices to detect model misspecification in Bayesian PGMs. Second, it is common to encounter missing data in longitudinal data analysis, and the presence of missing data will negatively impact the performance of those indices. Third, the performance of model fit and selection indices can depend on how prior distributions are specified. Here we conducted a simulation study to examine the impact of model misspecification and missing data on the performance of Bayesian model fit and selection indices (PPP-value, BCFI, BTLI, BRMSEA, BIC, and DIC), with an additional focus on prior sensitivity. The factors manipulated were sample size, missing data, knot placement, and specification of prior distributions. Results indicated that the performance of model fit and selection indices was exacerbated as the degree of model misspecification and amount of missing data increased. In addition, we found advantages of different prior specifications for certain conditions in model selection. We recommend researchers use available model fit and selection indices as a model comparison toolbox. Detailed guidelines for researchers and future research directions are provided. We are hopeful that this research can facilitate wiser implementation of Bayesian PGMs.

**Friday, 13:30-15:00, Session G-2: Growth Curve and Multi-Level Modeling II.** Chair: Jost Reinecke, "Long Table", Room 231 M

## Analyzing the development of legal norm acceptance by using a Bayesian second-order growth model with approximate measurement invariance

Bendler, Jasper
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Keywords: latent growth model, Bayesian structural equation modeling,approximate measurement invariance

Analyzing the development of latent constructs over time requires the existence of at least scalar longitudinal measurement invariance (MI). If scalar MI is absent, no valid comparison should be made and the results must not be interpreted. The Bayesian framework offers the possibility of a less stringent understanding of MI, called approximate MI, in which a small difference between factor loadings and/or intercepts is allowed. Using data from the panel study crime in the modern city (CRIMOC) including over 3,000 participants and eight panel waves, an example for a second-order growth model with longitudinal approximate metric and scalar MI for the development of legal norm acceptance in adolescence will be presented. The results indicate a curvilinear development of legal norm acceptance, with a minimum at the age of 15.

**Friday, 13:30-15:00, Session G-2: Growth Curve and Multi-Level Modeling II.** Chair: Jost Reinecke, "Long Table", Room 231 M

## Modelling two time-varying indicators measured in real-life – teachers' physiological stress and affect

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***Keywords:*** multilevel SEM, continuous time modeling, situational stress, situational affect, intraindividual relations

Associations between physiological and affective stress responses have been studied quite widely, although less is known about the intraindividual relations. In the literature, mostly hierarchical linear modelling with one (time)dependent variable has been applied. Studies of situational affect predicting physiological stress levels have mostly measured affect and cortisol at exactly the same time, without considering the time lag between affect observations and cortisol sampling. In real-life data collection (e.g on workdays and in ambulatory settings) it is difficult to ensure the exact same time stamps for two or more time-varying indicators of interest.

We aimed to study the within-person relations between teachers' situational physiological stress and affect during the school day. In two working days, 61 teachers from Finnish primary schools gave six saliva samples and answered to affect questionnaire four times a day. We faced two analytical problems with our data. First, in many cases, there was a time lag between the cortisol sampling and affect observations. Second, the hen and egg problem arose while designing a regression model for cortisol and affect.

Here we would like to present a multilevel structural equation model that includes cortisol, with time since awakening as a flexibly coded time-varying covariate predicting affect with time since cortisol measurement as a time-varying covariate. We excluded affect observations collected before the cortisol sampling from the data set.

We are showing one option for modeling two or more time-varying indicators concurrently in a multilevel SEM framework, and discuss the data linking and exclusion criteria. We hope to continue academic discussions about combining different indicators in intraindividual research. Substantively, our study showed that despite teachers' average levels of physiological stress and affect, their higher cortisol levels are related to experiencing less positive (e.g., enthusiasm) and more negative (e.g., nervousness) affect at a situational level

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