Rheinland-Pfälzische Technische Universität Kaiserslautern Landau

The Effect of Sampling Frequency on Careless Responding in an Ambulatory Assessment Study:

An Application of Multigroup Multilevel Latent Class Analysis

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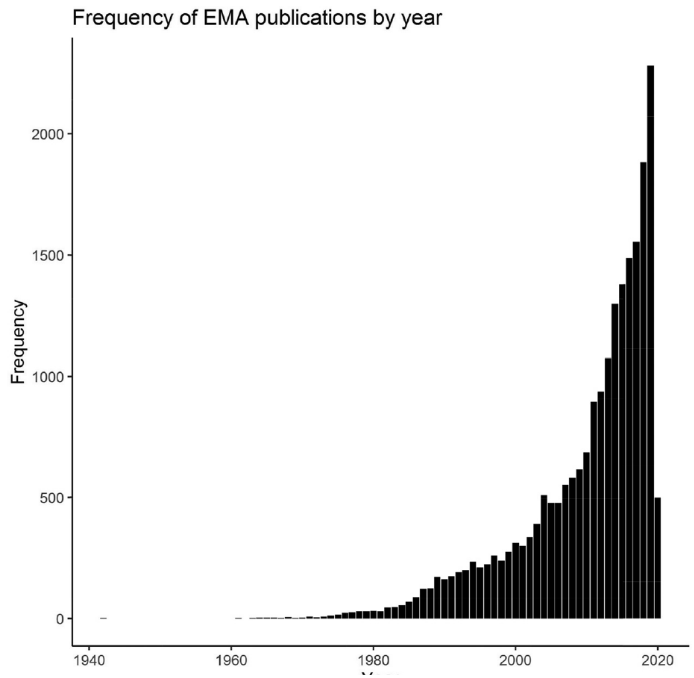
STATISTICAL MODELING in PSYCHOLOGY
FREIBURG HEIDELBERG LANDAU MANNHEIM TÜBINGEN

What is Ambulatory Assessment?

- *Ambulatory Assessment* [experience sampling (ESM), ecological momentary assessment (EMA), daily diary]
  is a method for assessing daily life experiences, for example, the ongoing behavior, experience, physiology, and environmental aspects of people in naturalistic and unconstrained settings (Fahrenberg, 2006)



Background

- Design choices in an Ambulatory Assessment (AA) study e.g.:
  - Number of days to survey people
  - Questionnaire Length
    (Number of items to administer per questionnaire)
  - Sampling Frequency (SF)
    (Number of questionnaires to administer per day)

→ Keep balance betweeen:

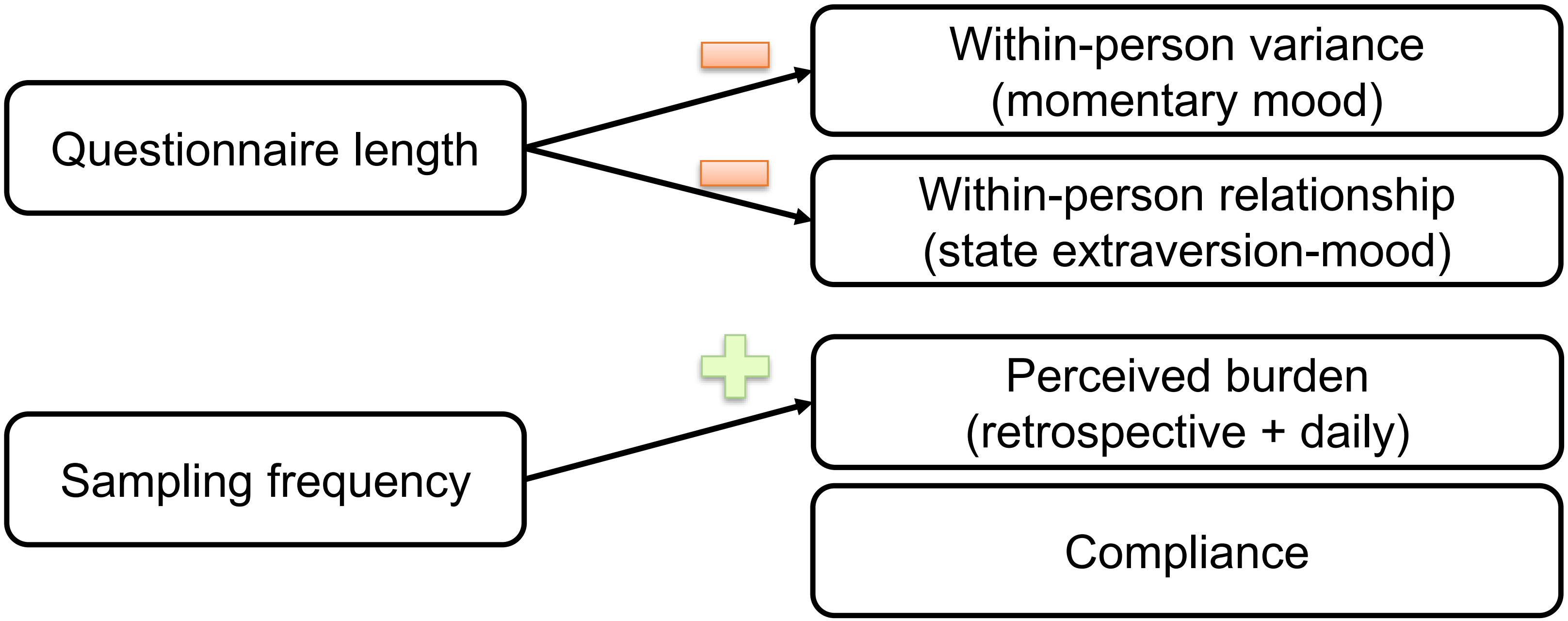
Rich information vs. Overburdening participants (Carpenter et al., 2016)

Compromising data quality (Arslan et al., 2020)

Little is known about the effects of the design choices on…

Eisele et al., 2020

Hasselhorn, Ottenstein, & Lischetzke, 2022



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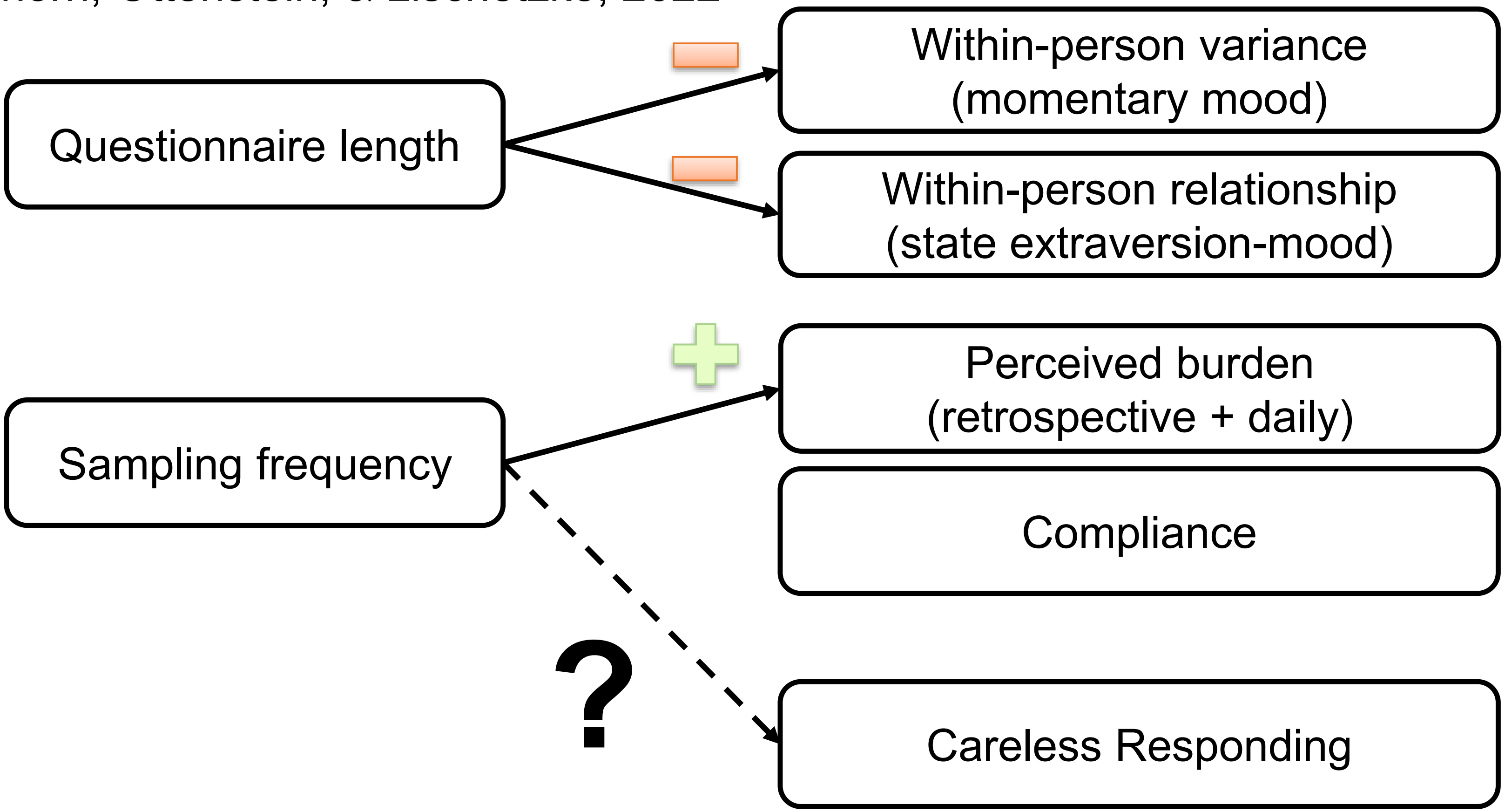


Little is known about the effects of the design choices on…

Eisele et al., 2020

- Careless responding (CR) [Insufficient Effort Responding]
  - Refers to participants responding without (sufficient) regard to the item content (Huang et al., 2012; Meade & Craig, 2012)
  - Threatens construct validity
  - Can inflate or attenuate correlations between substantive measures (Huang et al., 2015; McGrath et al., 2010)

What has been done?

- CR is well-researched in cross-sectional research (Meade & Craig, 2012)

- CR can be identified in surveys using Latent Class Analysis (LCA) (e.g. Goldammer et al., 2020; Kam & Meyer, 2015; Maniaci & Rogge, 2014; Meade & Craig, 2012)
  - LCA identifies subtypes of observation units that show similar patterns of scores on observed indicators
  - Participants can be assigned to one of three classes
    - Careful responders
    - Long string [invariant] responders
    - Inconsistent [random] responders

→ Can we translate these findings to AA (measurement occasions nested in participants)?

What has been done?

- How can we identify CR in AA?

→ cross-sectional research uses CR indices as observed indicators in LCA

  → Direct [obstrusive] measures of CR
    - Rely on self-reports
  - Indirect [unobstrusive] measures of CR
    - Analyse response behavior

- Can we translate these CR indices to AA (measurement occasions nested in participants)?

- CR received relatively little attention in the AA literature
  - Eisele et al. (2020) found no effect of the Sampling Frequency on CR using direct measures

  → No research on latent class structure in AA

Our aims

- 1) Apply LCA to AA data (measurement occasions nested in participants) to…
  - … identify momentary careless and careful responding profiles (Level 1)
  - … identify classes of individuals (Level 2) who differ in the use of the momentary careless responding profiles over time

- 2) Investigate the impact of (experimentally manipulated) Sampling Frequency on CR

- 3) Investigate the impact of covariates on latent profile (Level 1) and latent class (Level 2) membership

Model CR in AA

- We identified these four CR indices:
  – Average longstring index
  – “Occasion-person correlation” (cf. “person-total correlation” in cross-sectional surveys)
  – Response time (detrended RT)
  – Inconsistency Index (number of illogical responses across 4 pairs of reverse-poled mood items)

- All indices coded so that **higher scores represent more careless responding**

Study 1 - design

1 week

L(ow) **SF G**(roup) | **3** measurement occasions/day

H(igh) **SF G**(roup) | **9** measurement occasions/day

- Manipulated SF

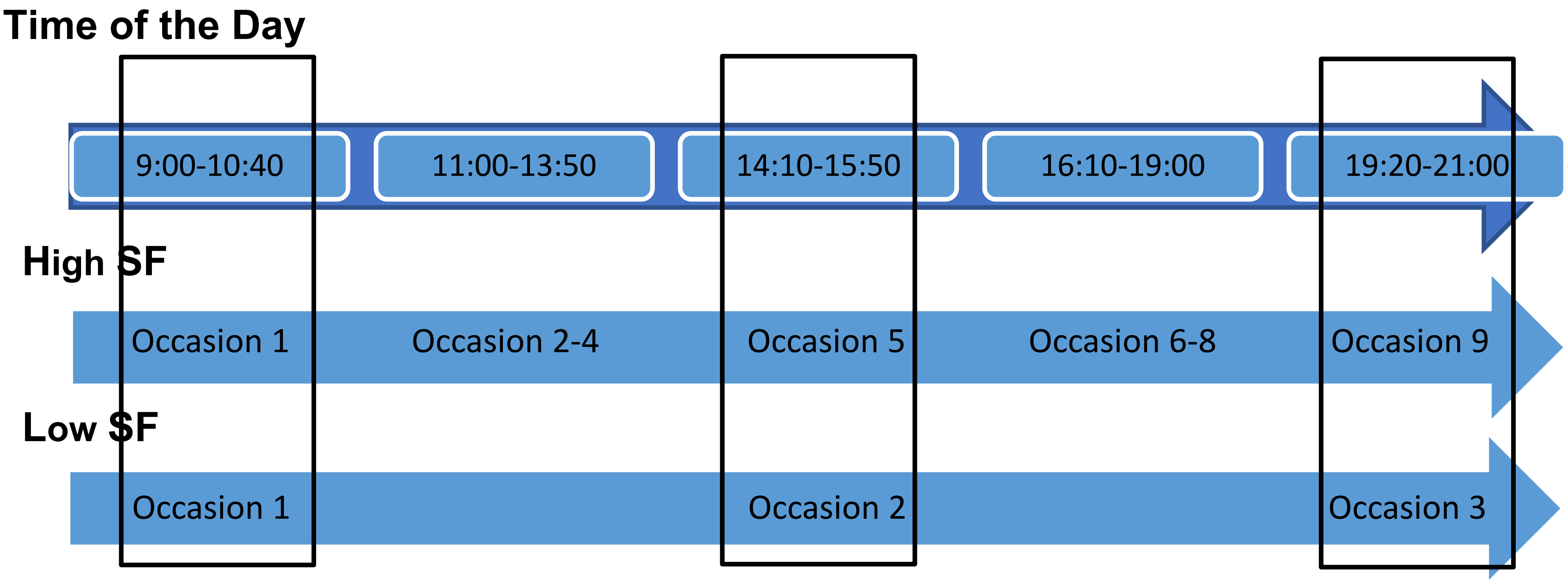
- Each measurement occasion/day
  - Setting + momentary motivation
  - Momentary mood
  - State extraversion + conscientiousness
  - Stress (1x per day)
  - Perceived burden through study participation (1x per day)

4 CR indices
- Longstring index
- Occasion-person correlation
- Response time
- Inconsistency Index

- 313 students
  - 84% women; age Range: 18 to 40 years, M = 23.58, SD = 3.73

SMiP

Study 1 – design



- All estimates are based on **three occasions**

Data Analytic Methods

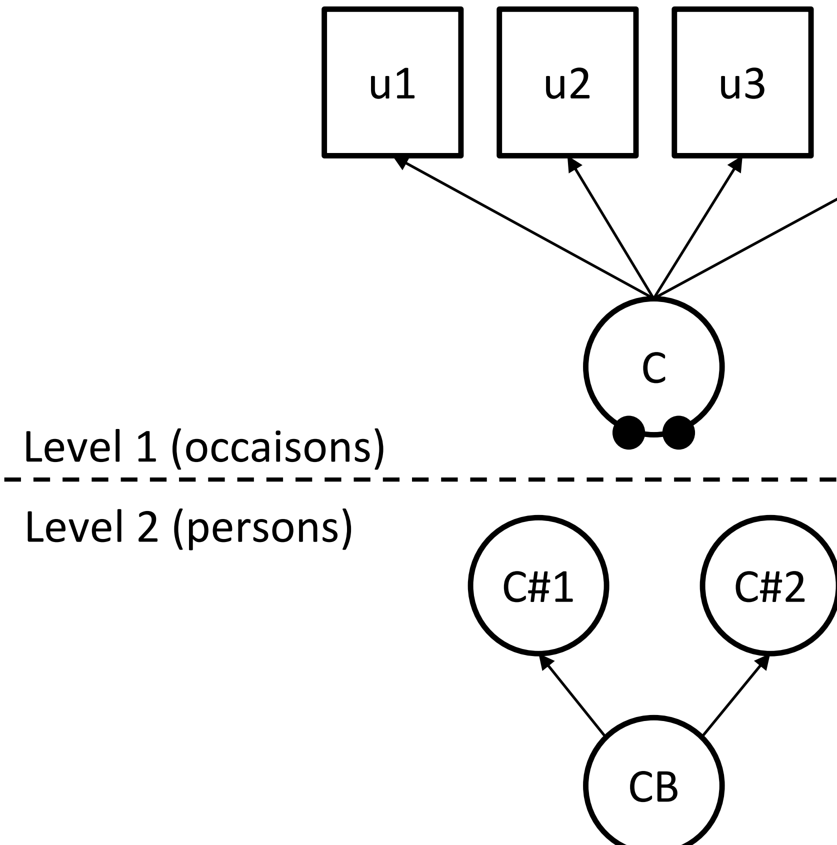
Aim 2) Investigate the impact of SF on CR

→ Multigroup ML-LCA – no previous research

Data Analytic Methods

Aim 2) Investigate the impact of SF on CR

→ (ML-) LCA



u1-u4 : CR indices

C: Latent class variable (at Level 1): types of occasions differing in the configuration of observed indicators

CB: Latent class variable at Level 2: types of persons differing in the distribution of Level-1 classes/profiles

Data Analytic Methods

Aim 2) Investigate the impact of SF on CR

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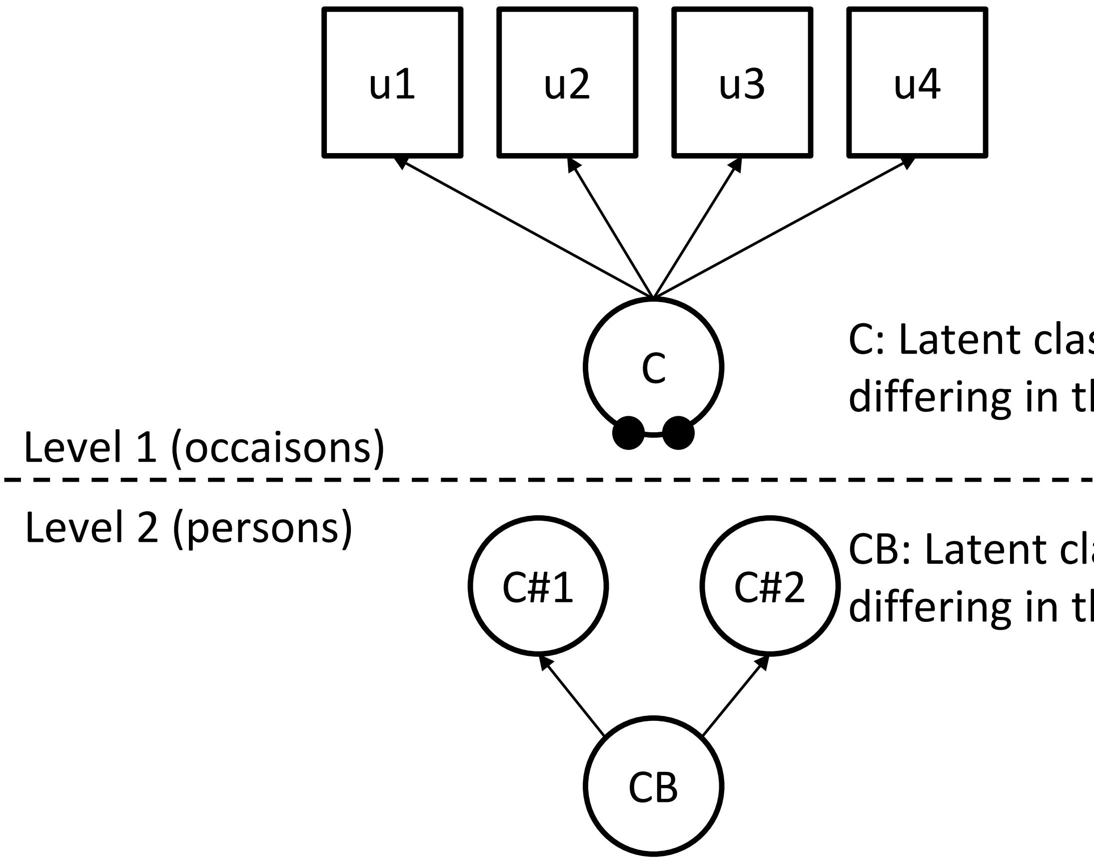

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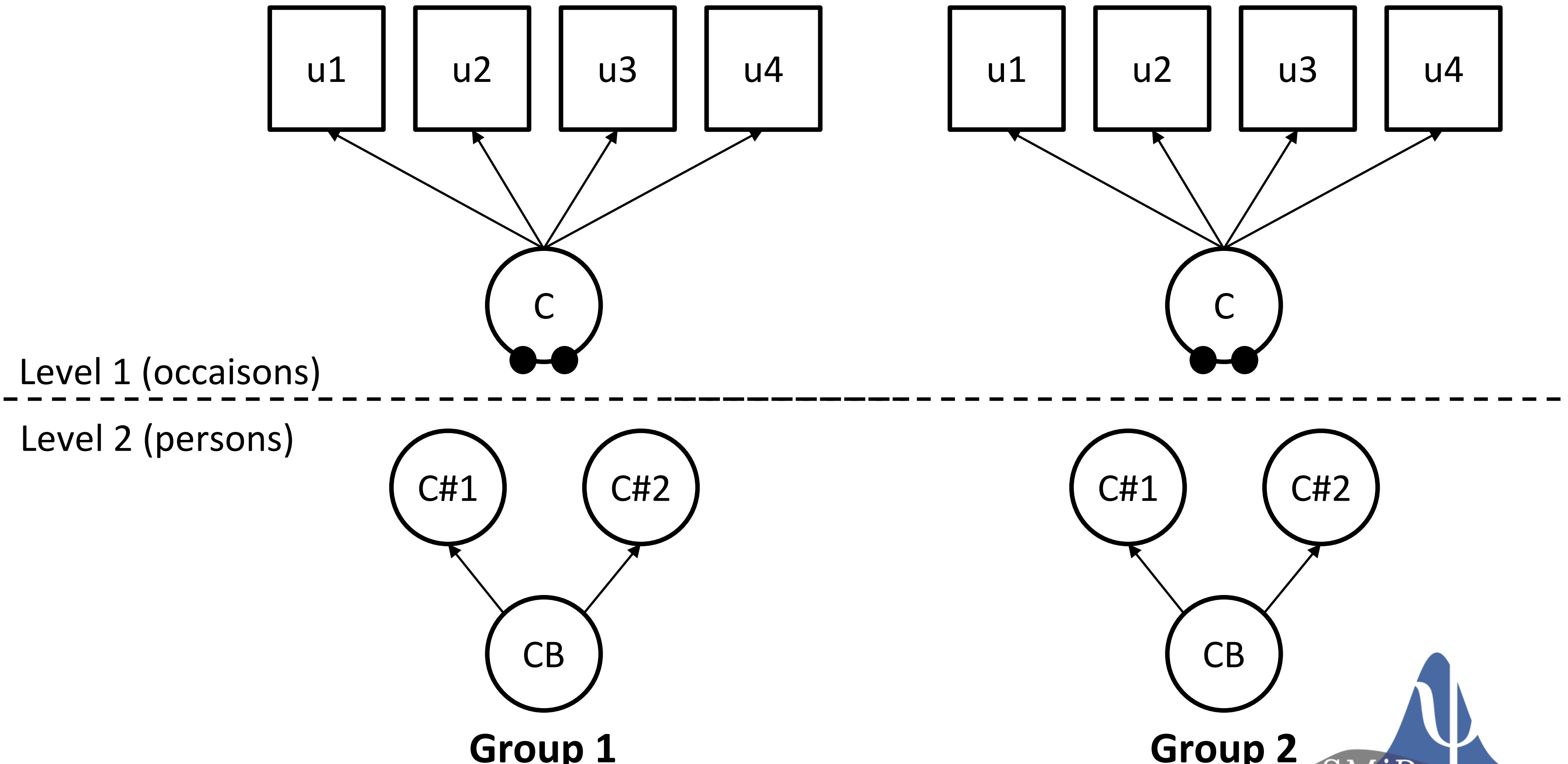


Data Analytic Methods

Aim 2) Investigate the impact of SF on CR

- Multigroup ML-LCA
  - Level 1: Classes (profiles) of momentary careful vs. careless responding
  - Level 2: Classes of individuals who differ in the distribution of Level 1 profile membership over time
  - Level 2 Class sizes

- General procedure for standard multigroup LCA recommended by Eid et al. (2003) and Kankaraš et al. (2010)
  - 1st step: Estimate optimal class solutions for each experimental group
  - 2nd step: Analyze different degrees of measurement invariance across experimental groups

Data Analytic Methods

- Four MG-ML-LCA models differing in equality restrictions across groups:

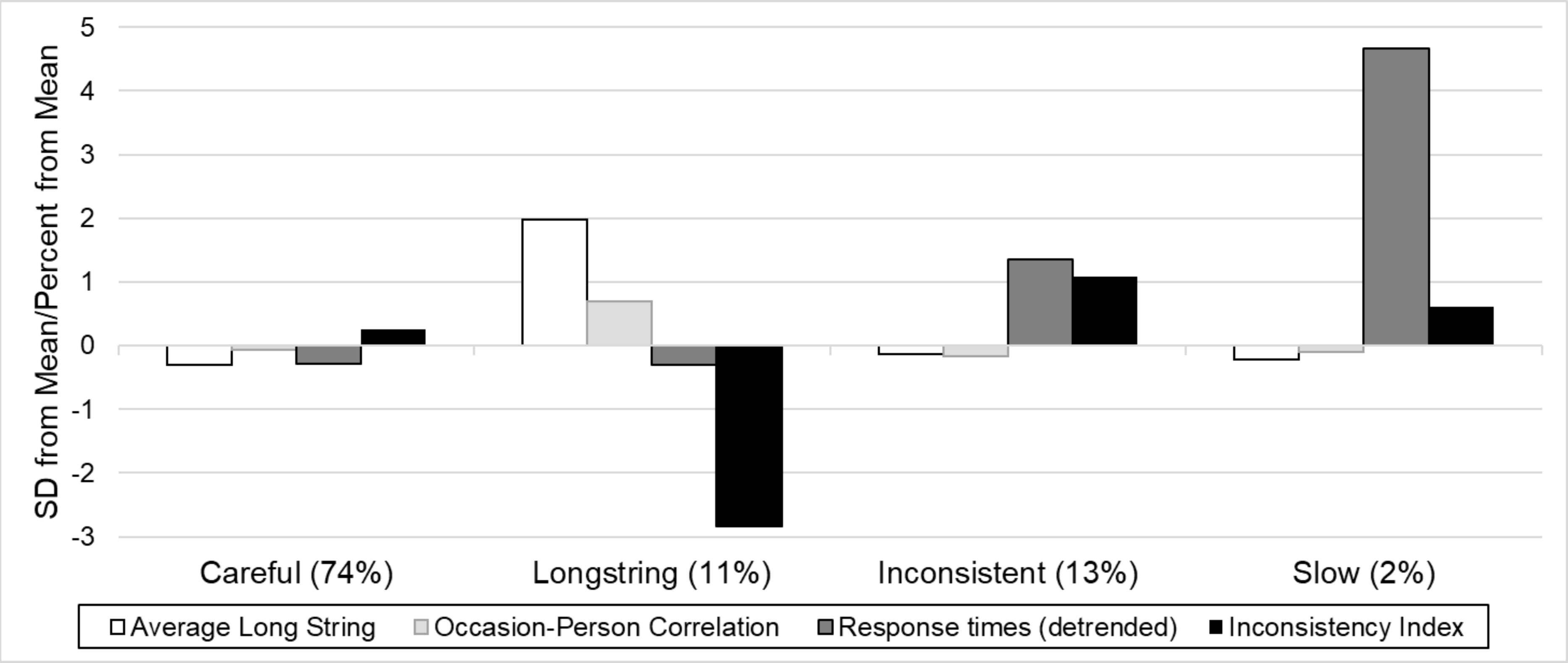
	Hetero-geneous	Partially homogen. **A**	Partially homogen. **B**	Fully homogen.
Measurement model parameters at Level 1 (i.e., definition of Level 1 profiles)		X	X	X
Measurement model parameters at Level 2 (i.e., definition of Level 2 classes)			X	X
Class sizes at Level 2				X

X = set equal across groups

SMiP

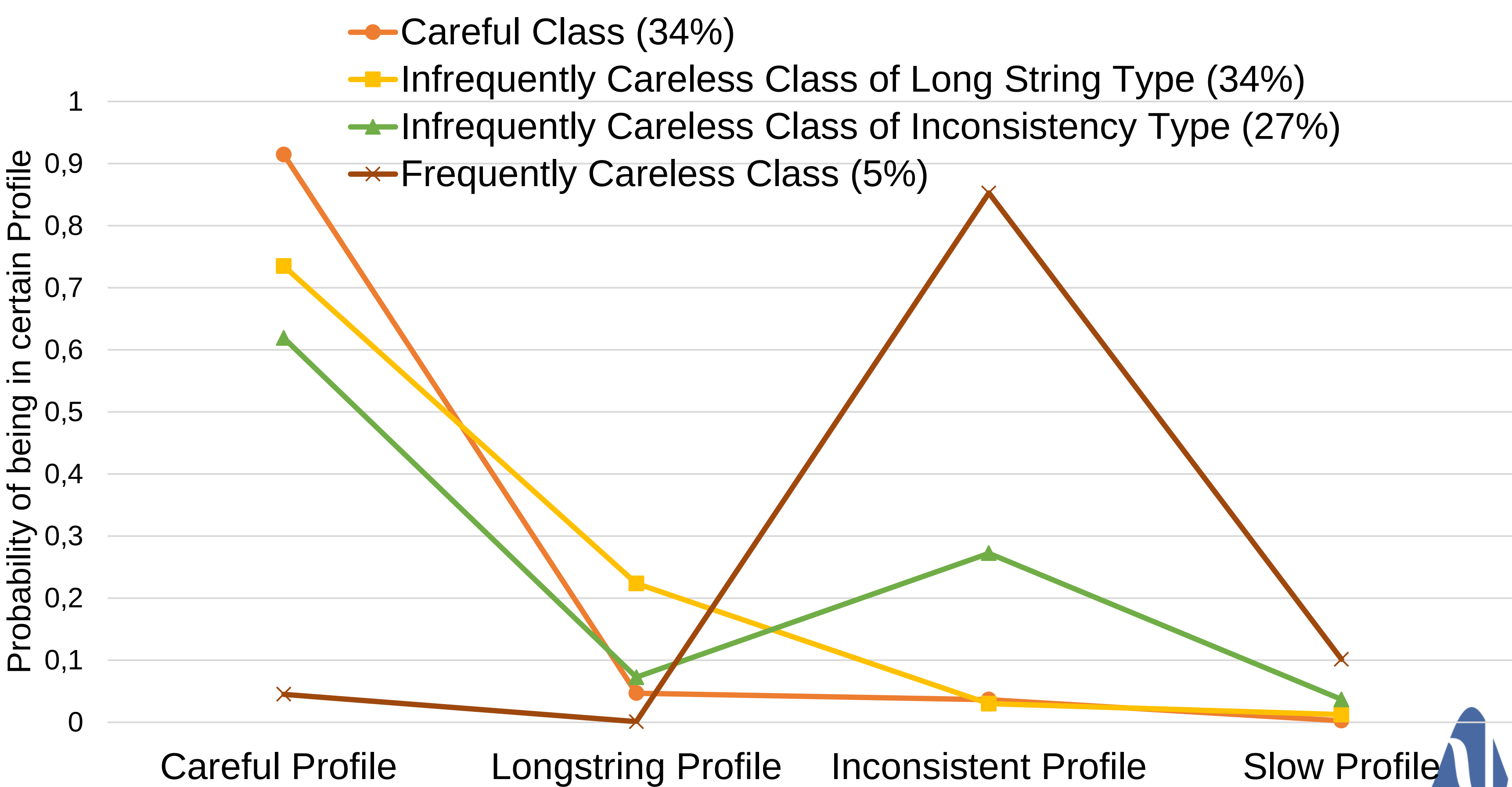
Results ML-LCA

Profiles (Level 1): Low Sampling Frequency Group: 4-profile solution fitted the data best



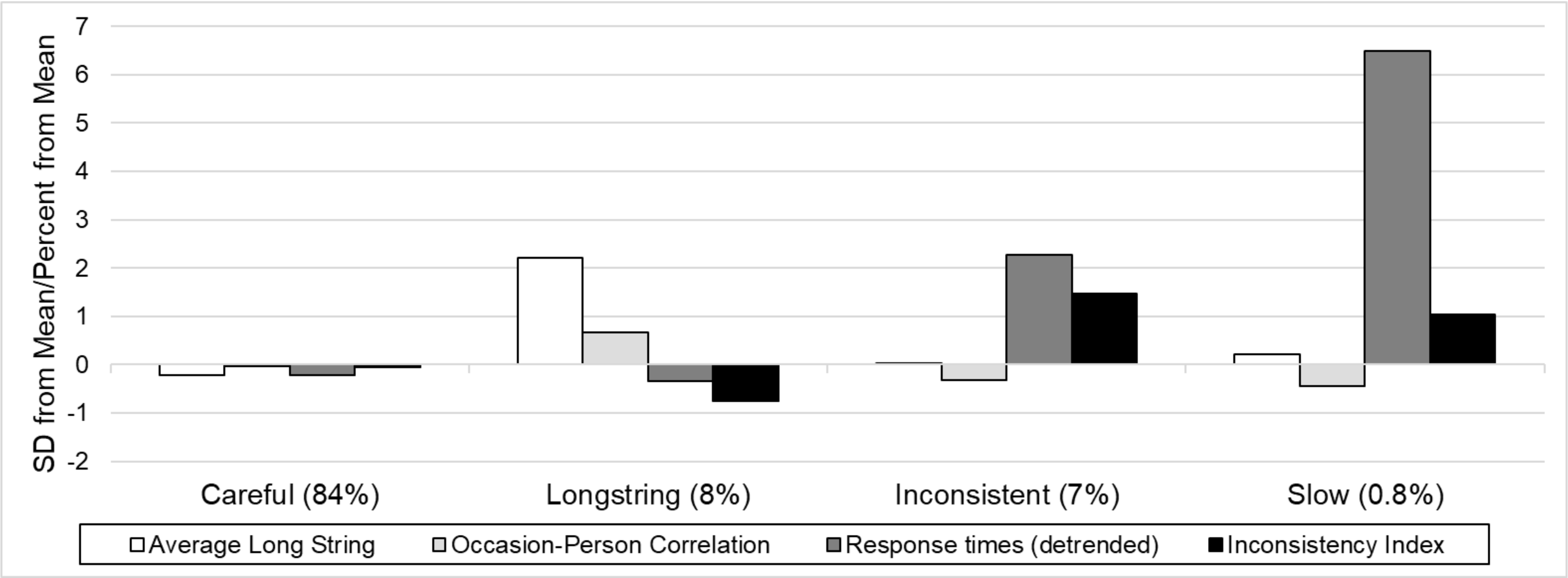
Results ML-LCA

Classes (Level 2): Low Sampling Frequency Group: 4-class solution fitted the data best



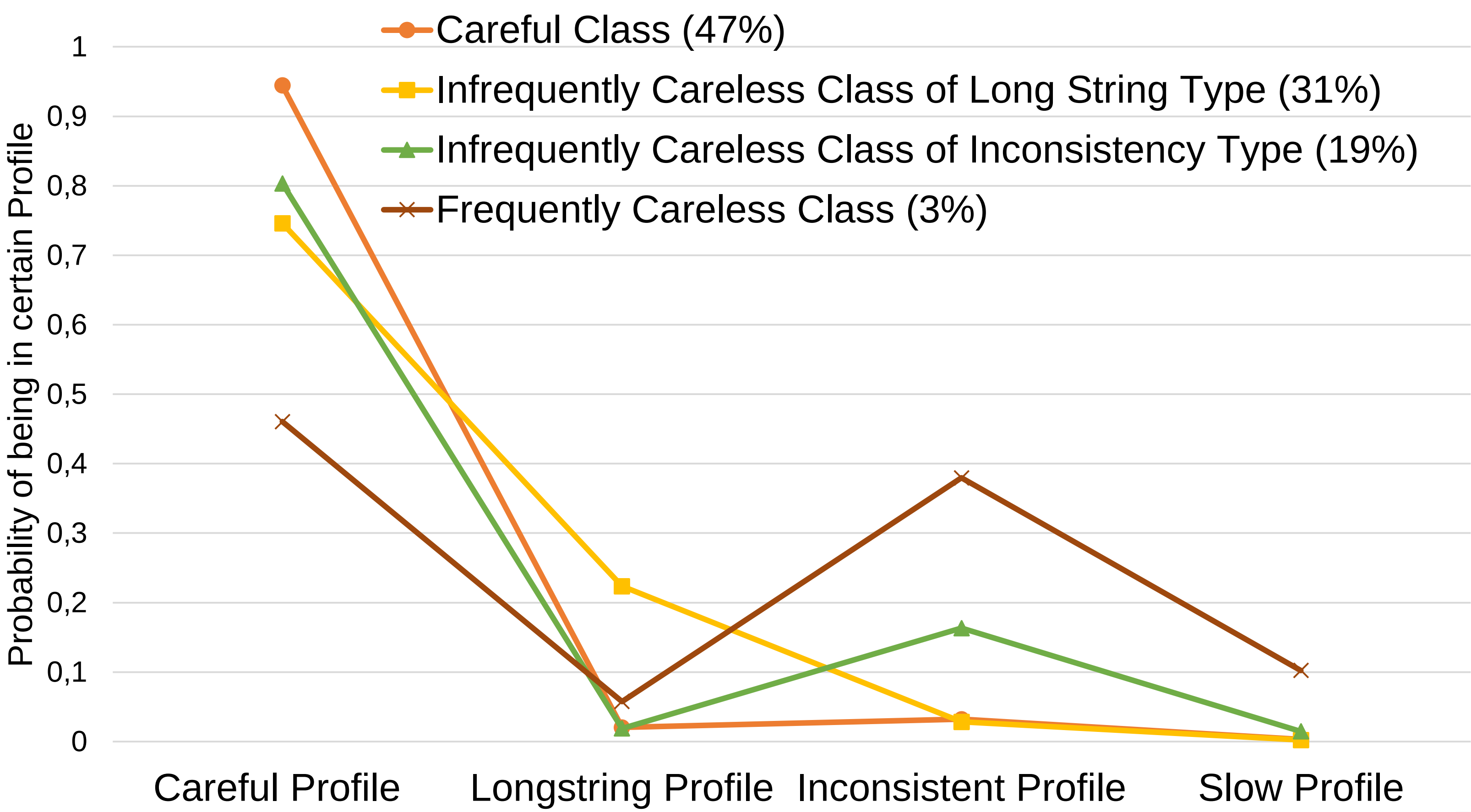
Results ML-LCA

Profiles (Level 1): High Sampling Frequency Group: 4-profile solution fitted the data best



Results ML-LCA

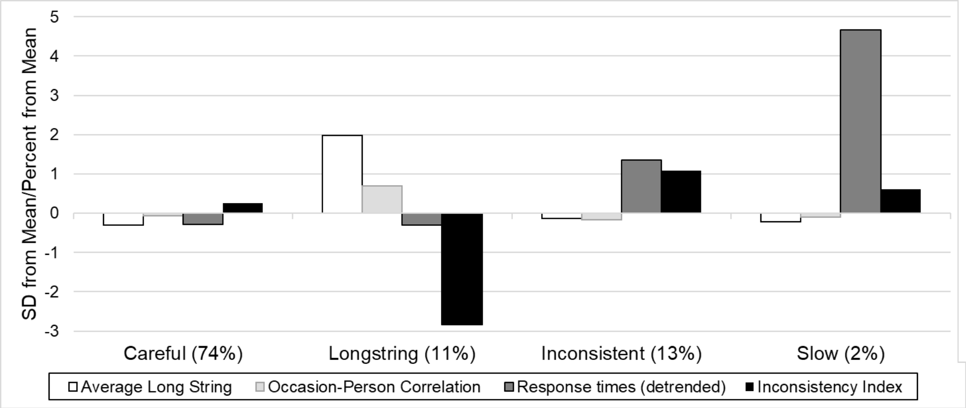
Classes (Level 2): High Sampling Frequency Group: 4-class solution fitted the data best

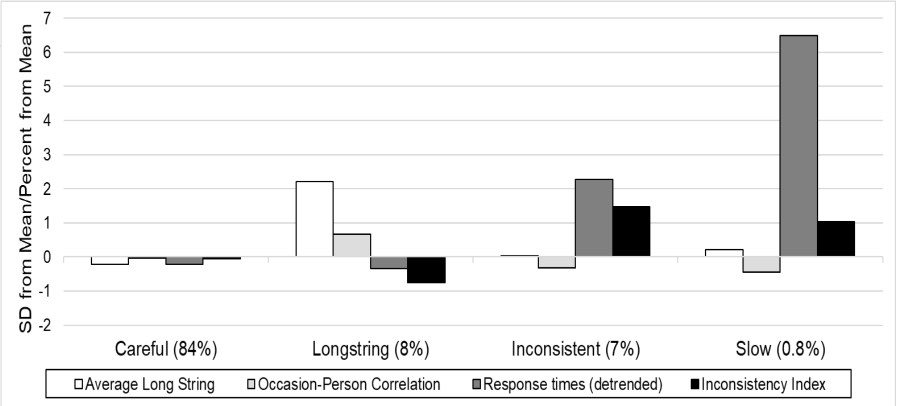


Results ML-LCA

Profiles (Level 1):

Low Sampling Frequency Group vs. High Sampling Frequency Group

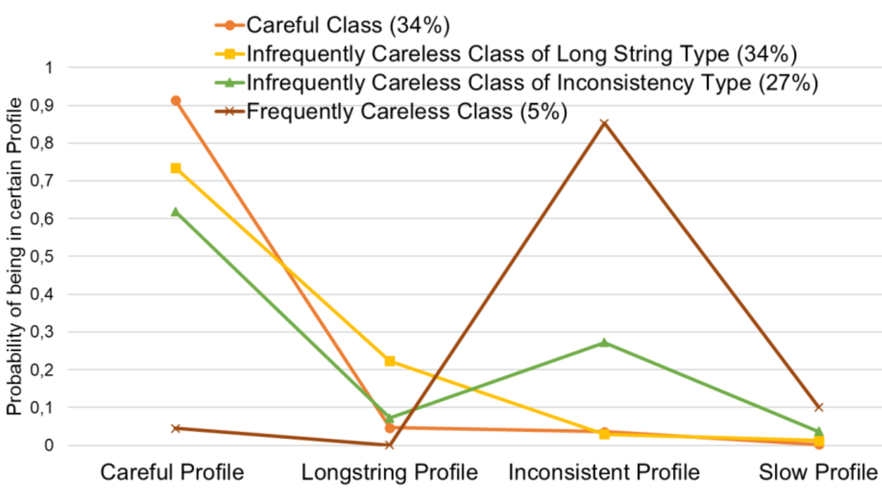


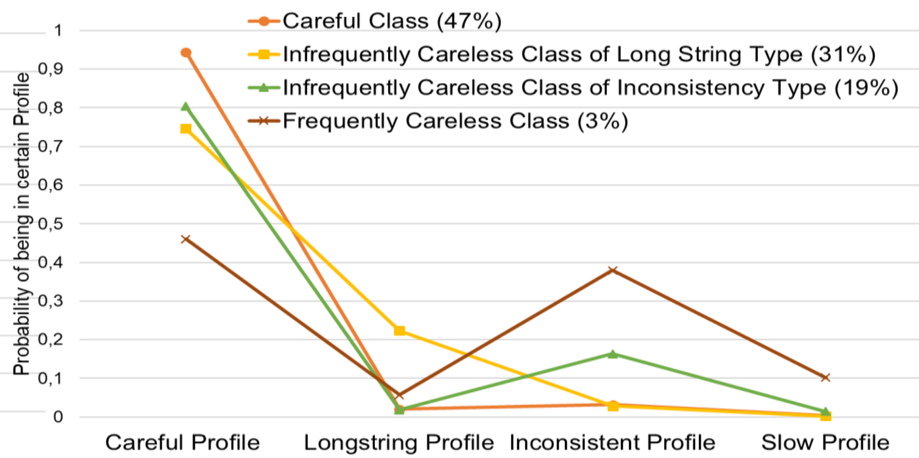


Results ML-LCA

Classes (Level 2):

Low Sampling Frequency Group High Sampling Frequency Group





→ Differences between the groups are mostly in the High Careless Class

Results multigroup ML-LCA

Aim 2)

- Fully homogeneous model provided the best fit in terms of the BIC

	Hetero-geneous	Partially homogen. **A**	Partially homogen. **B**	Fully homogen.
Measurement model parameters at Level 1 (i.e., definition of Level 1 profiles)		X	X	X
Measurement model parameters at Level 2 (i.e., definition of Level 2 classes)			X	X
Class sizes at Level 2				X

X = set equal across groups

→ We can assume measurement invariance across experimental groups

Results multigroup ML-LCA

Aim 2)

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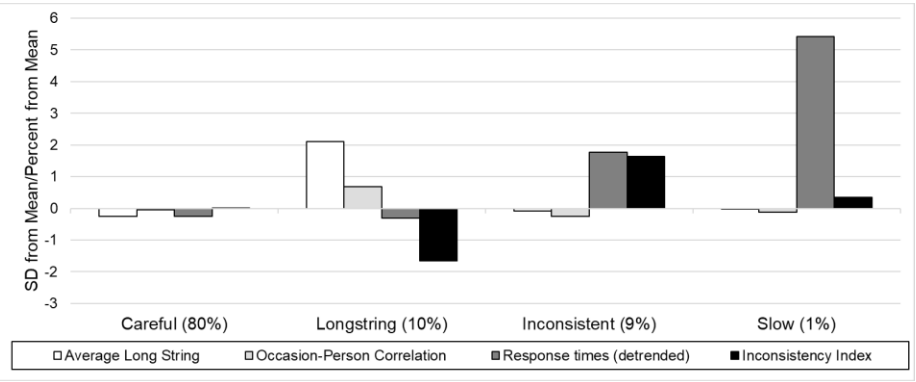

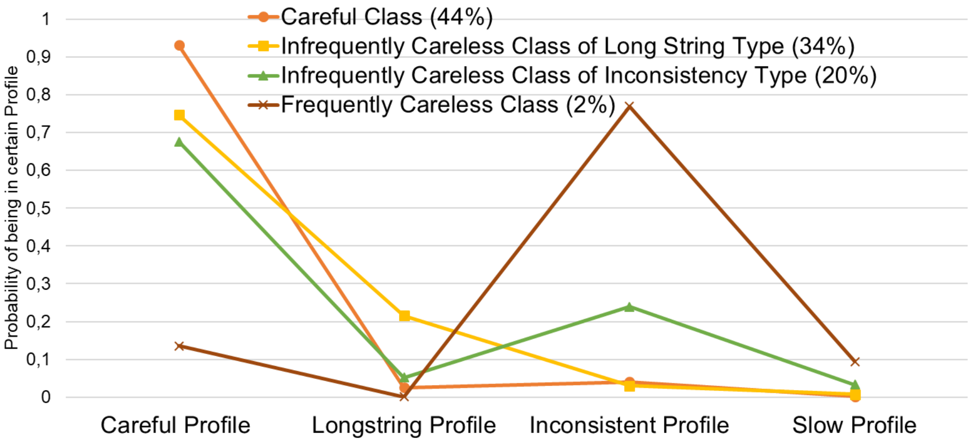

→ We can assume measurement invariance across experimental groups

Results covariate analyses

Aim 3)

- Aggregated momentary motivation +
- Doing the reseacher a favor (motivation for study enrollment) were significant
- All other covariates remained non significant

	Classes of Individuals			
Covariate	Wald test χ^2	*df*	*p*	R^2
Aggregated momentary motivation	36.39	3	< .001	0.072
Motivation for study enrollment				
Doing the researcher a favor	20.87	3	< .001	0.027

- The Differences were between the High Careless Class and all other classes for both covariates

Discussion + Future directions

- Momentary careless and careful responding profiles (Level 1) and classes of individuals (Level 2) can be identified in at least one AA study
  - Stability across other AA studies?

- There is no effect of the SF on CR
  - In line with the study by Eisele et al. (2020)
  - Stability across other design features?

- Aggregated momentary motivation + Motivation for study enrollment (“Doing the reseacher a favor “) are possible covariates
  - What is the effect of other covariates?

Thank you!

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Prof. Tanja Lischetzke

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