Experimental evidence for a dynamic latent class model of non-compliance

Patrick Schmidt[1] Zachary Roman[1]
Jason Miller[2] Holger Brandt[3]

University of Zurich[1]
University of Kansas[2]
University of Tübingen[3]

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- Dynamic: Subjects can start and stop paying attention
- Goal: Model inattention to improve inference

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- General model of inattention with no assumption on responses
- Simulation evidence
- Experimental evidence:
  - MTurk survey randomly prompts inattention
  - generates realistic inattentive behavior
  - our dynamic model outperforms static model and standard cfa model

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  - random item order
  - two additional bogus items
- Control group: Standard (or prompted to pay attention)
- Treatment group: At random point in survey prompted to stop paying attention

> "Answer the rest of the questions with **no effort at all**."

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- Transition model: $P(C_t = 1 | C_{t-1} = 1, x_t) = f(\beta_0 + \beta x_t)$

Estimation

- We compare three Bayesian models on the experimental data
  - dynamic model
  - static model (Roman et al., 2022)
  - standard cfa (including pre-selection criteria)

- Bayesian inference with MCMC implemented in JAGS (Plummer, 2003)

Results: Attention classification

- Is the model able to detect the inattention treatment (red line)?

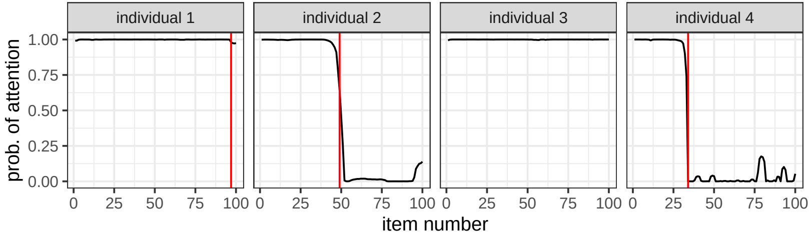

Figure: Posterior probability of attention over the course of the survey. Plot depicts four random subjects.

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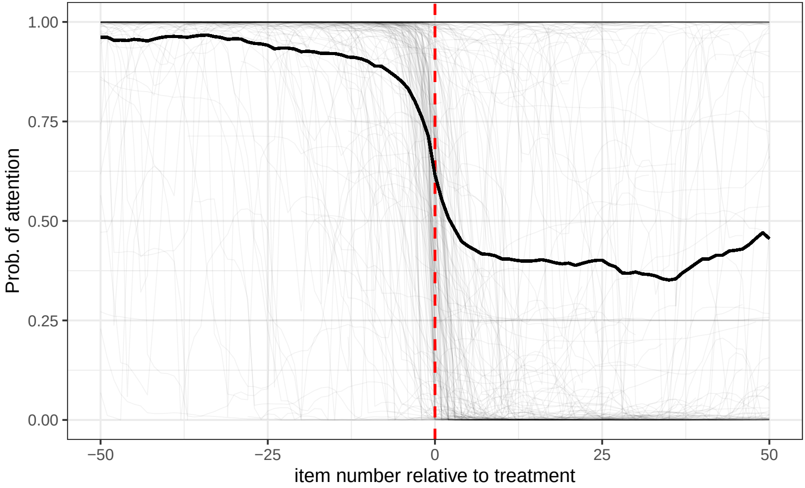
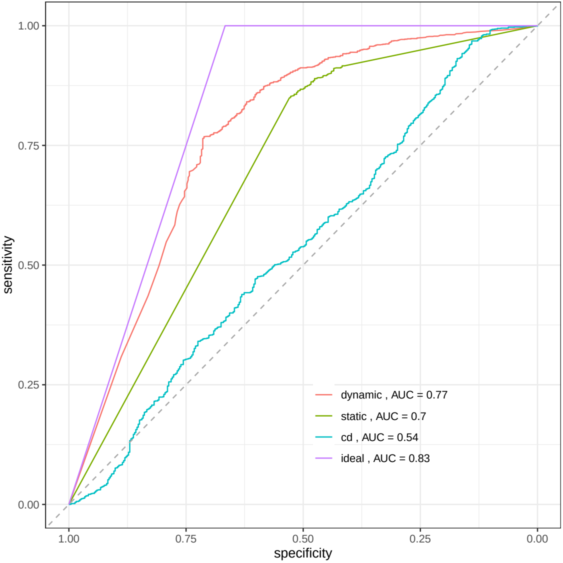
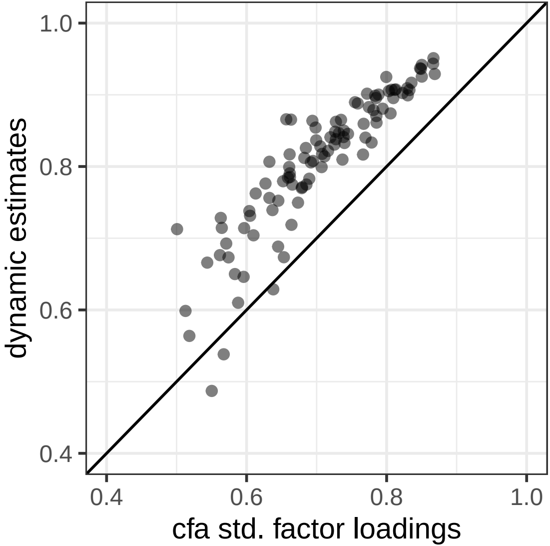


Results: ROC curve for predicting bogus items



Results: Estimation efficiency for factor loadings



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- Future work:
  - Extend computational feasibility
  - Comparison of importance of design choices

References I

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