On the importance of considering concurrent effects in random-intercept cross-lagged panel modelling

Example analysis of bullying and internalising problems in z-proso

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RI-CLPM

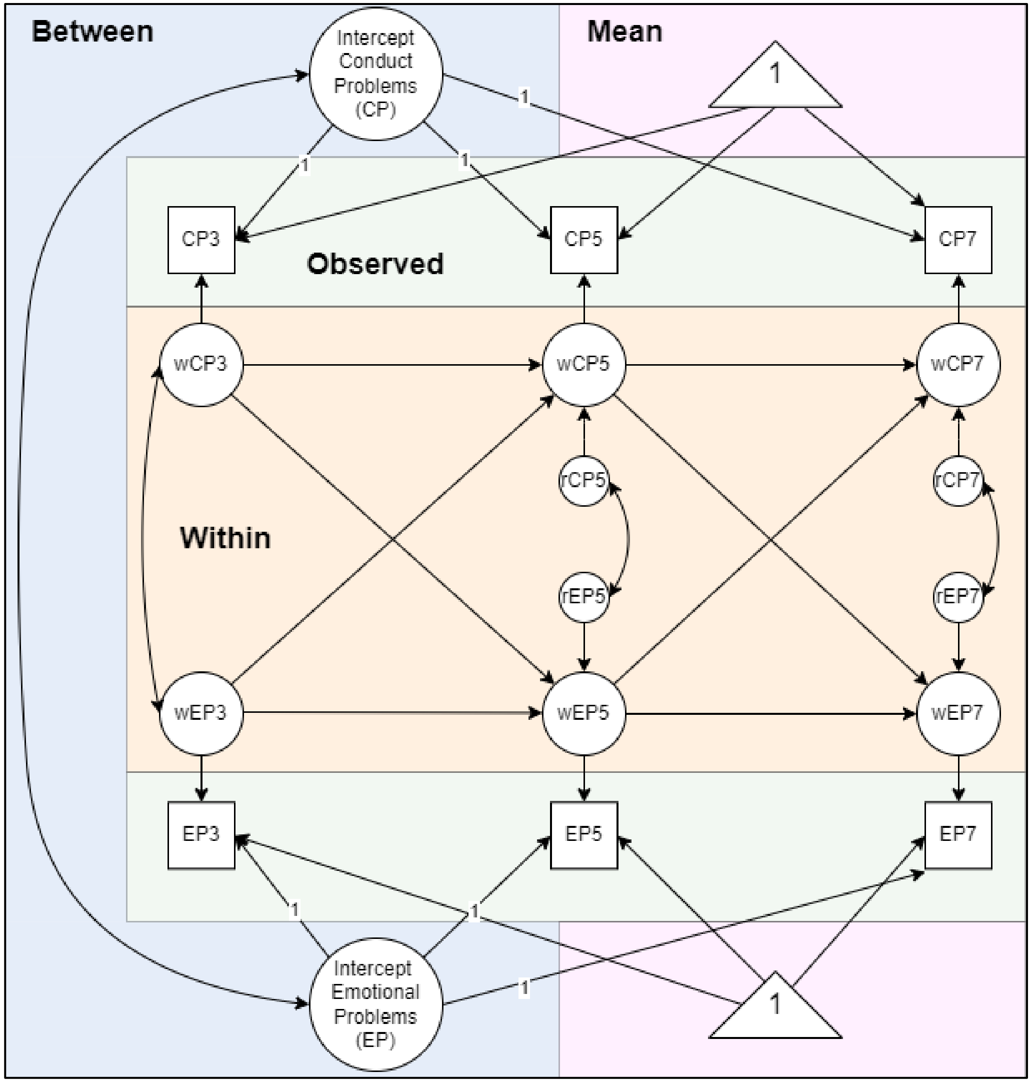
Decomposes observed variables into three components

- Grand means
  - means of all participants per time point

- Between-person components
  - Captured by random intercepts representing an individual's time-invariant deviations from the grand mean

- Within-person components
  - reflect the deviations of a person's observed scores from their expected mean score

→ **Autoregressive and cross-lagged effects can then be specified between the within-person components giving insights into within-person processes**



Can RI-CLPMs be relied on to establish causality?

- Basic criteria for establishing causality (John Stuart Mill)
  - A) Temporal precedence (i.e., the cause precedes the effect)
  - B) Empirically correlated (i.e., the cause and effect are associated with each other not just by chance)
  - C) There are no alternative explanations (i.e., no third variable accounts for the observed association).

- RI-CLPM supposedly:
  - A) Establishes temporal sequence
  - B) Empirically tests whether associations are due to chance
  - C) implicitly controls for between-person effects → reduces risks of unmeasured confounding

→ RI-CLPMs invite causal interpretations

Should we expect them to establish causality?

- RI-CLPMs were not designed as a causal inference method (unlike counterfactual analyses, mendelian randomization)
  - Designed as an improvement over CLPMs → improvement over linear regression (allow for transactional processes, control for prior levels of construct)

→RI-CLMPs focus on understanding the patterns of association and covariation between variables over time

Can RI-CLPMs be relied on to establish causality?

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  → What if the temporal sequence is misspecified? Concurrent effects?

  B) Empirically tests whether associations are due to chance

  → Measurement Error? Sampling bias? Power? Type 1 error?

  C) Reduces the risk of confounding by implicitly controlling for time-invariant between-person confounders that have stable effects on outcomes over time

  → What about time-varying confounders? When does a time-invariant confounder truly have a stable effect?

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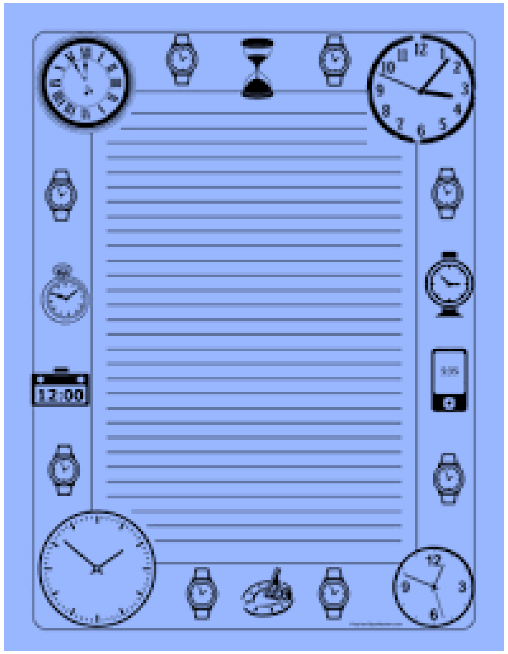
Concurrent associations?

- Temporal pathways may not always be clear cut…
- What if we use data that was measured at the same time-point but referred to different reference frames?
- For example, bullying measured over the past year vs anxiety over the past month?

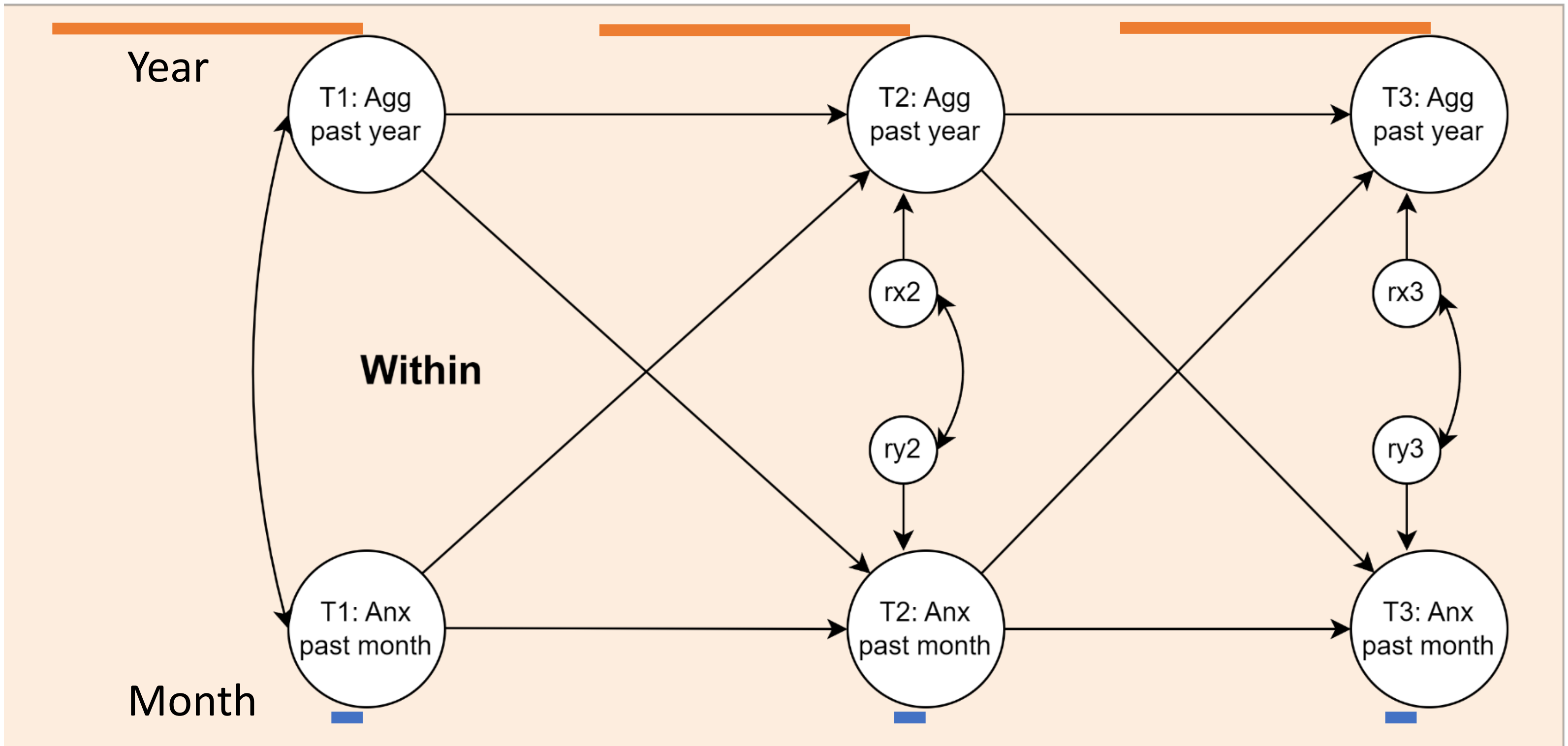
(Speyer et al., 2022)

Over what time-frames do we measure psychological constructs?

- External Experiences over the past year?
  - In z-proso: e.g., victimisation, substance use, prosocial behaviours, etc.
- Internal States over the past month?
  - In z-proso: e.g., anxiety, depression, ideations
- Constructs presumed to be stable? Measured without clear reference frame?
  - In z-proso: e.g., self-control, moral neutralization, self-efficacy



What if you were interested in analysing the reciprocal associations between aggressive behaviours and anxiety over time?



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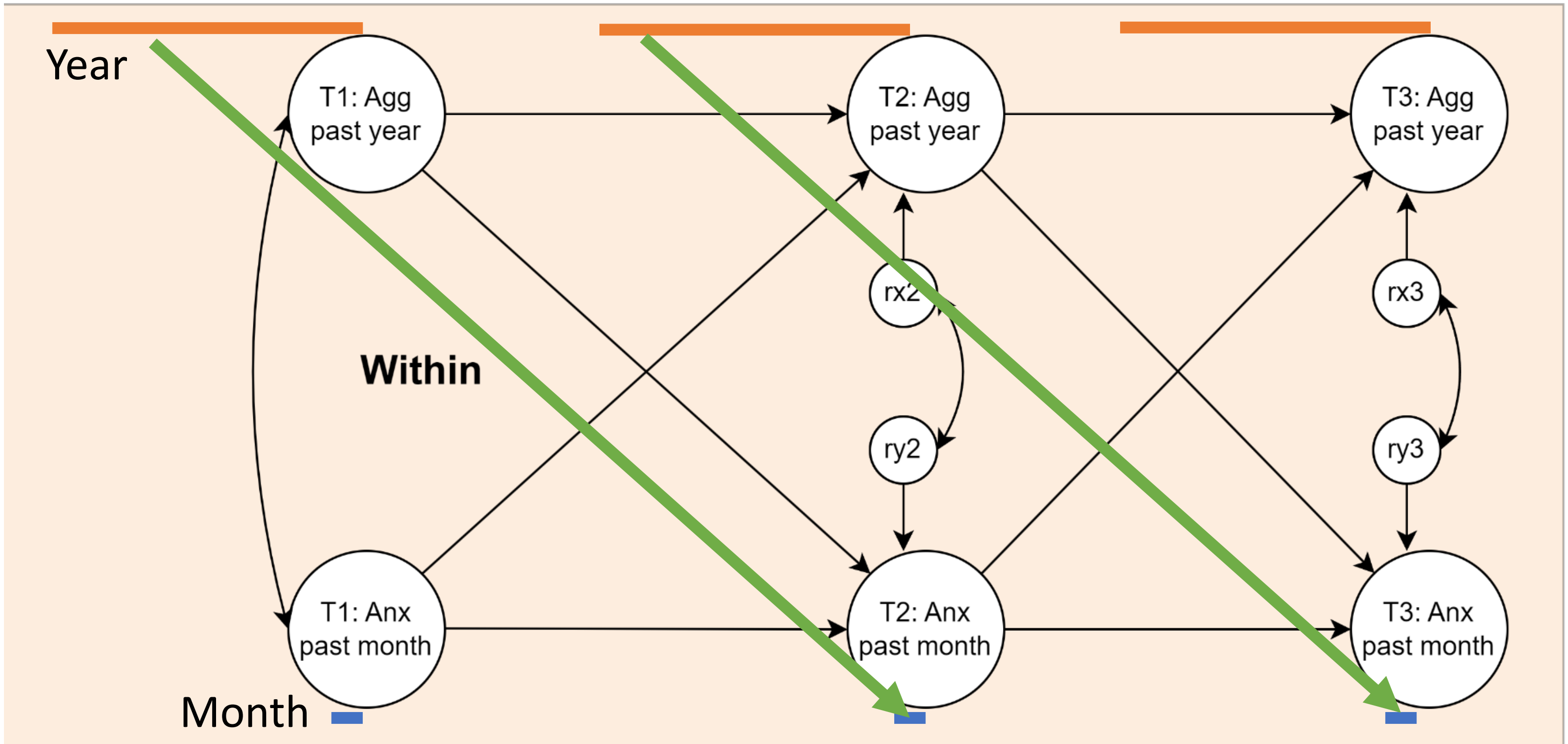


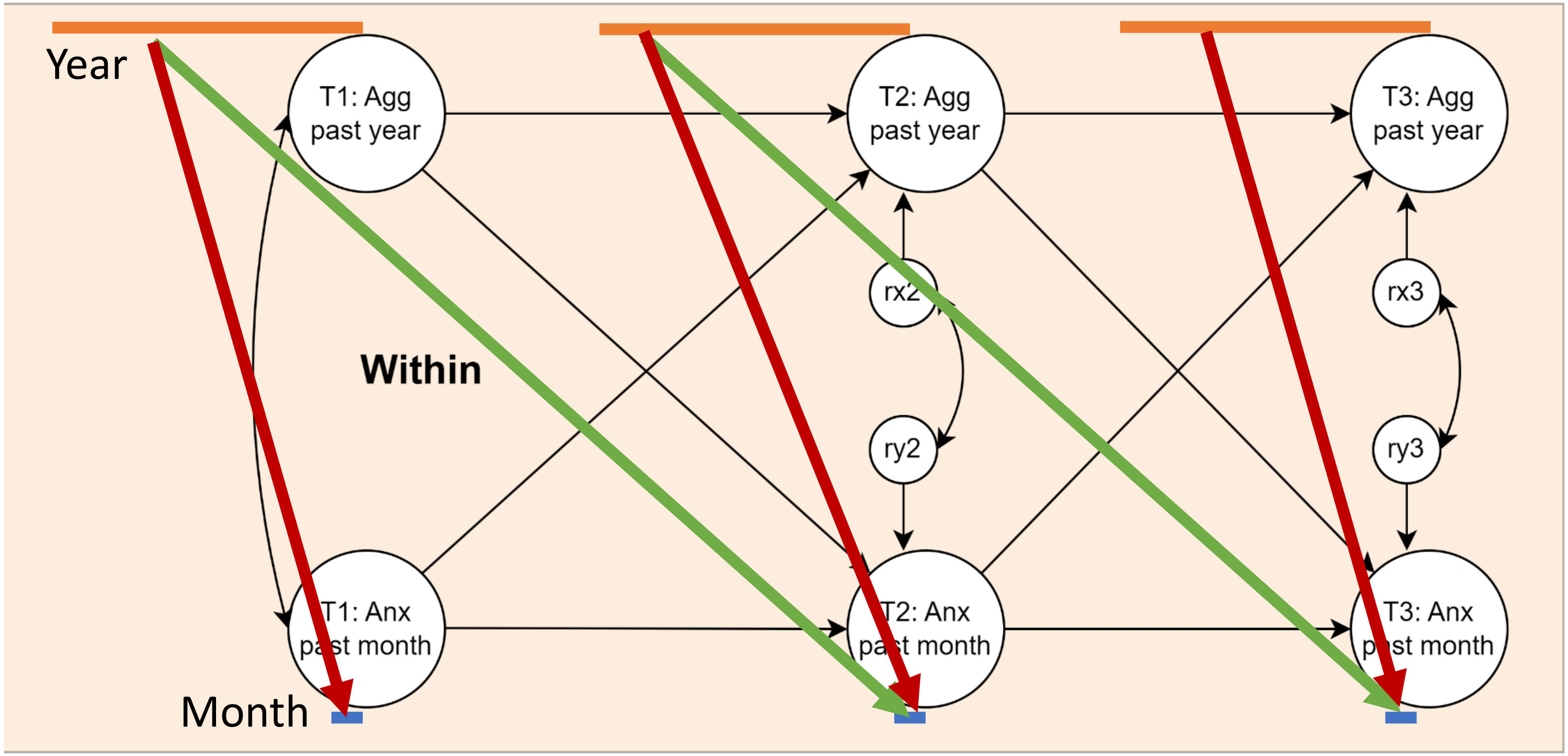
Does it make sense to treat within time-point associations purely as residual correlation? Are cross-lagged effects biased if only looking at residuals?

Counterintuitive Findings in RI-CLPMs

- Wiesner et al., 2022
  - upsurge in criminal offenses → subsequent reduction in mental health issues one year later
  - criminal offending measured over past year; mental health measured over past week,

- Zhu et al., 2022
  - increases in experiencing sexual bullying victimisation → subsequent reduction in suicidal ideations three years later
  - victimisation measured over the past year; internalising problems measured over past month

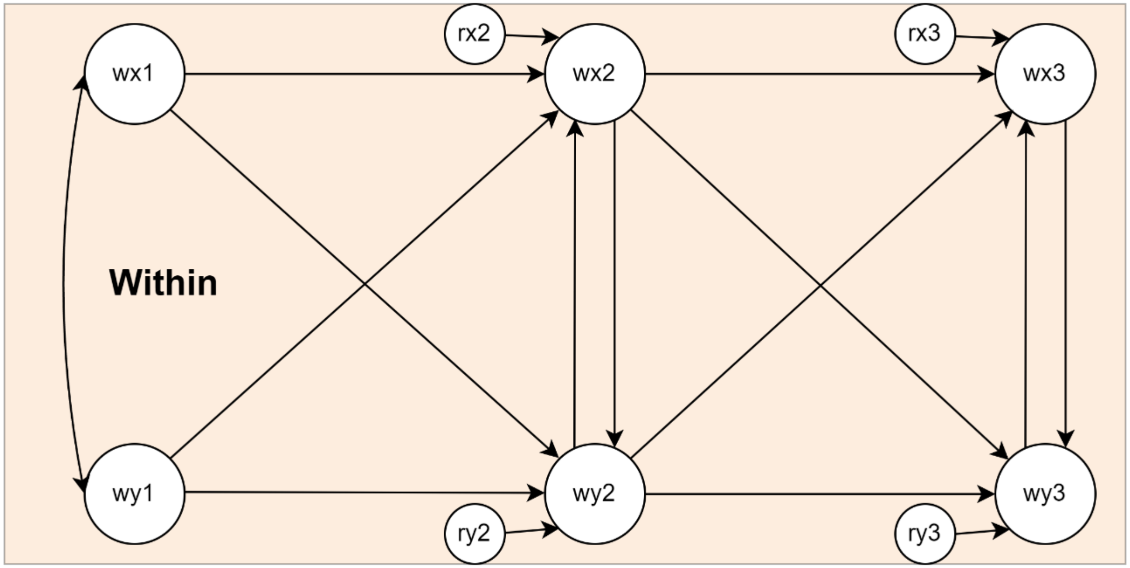
What if you were interested in analysing the reciprocal associations between aggressive behaviours and anxiety over time?



Reciprocal RI-CLPM

(Muthen and Asparouhov, 2022)

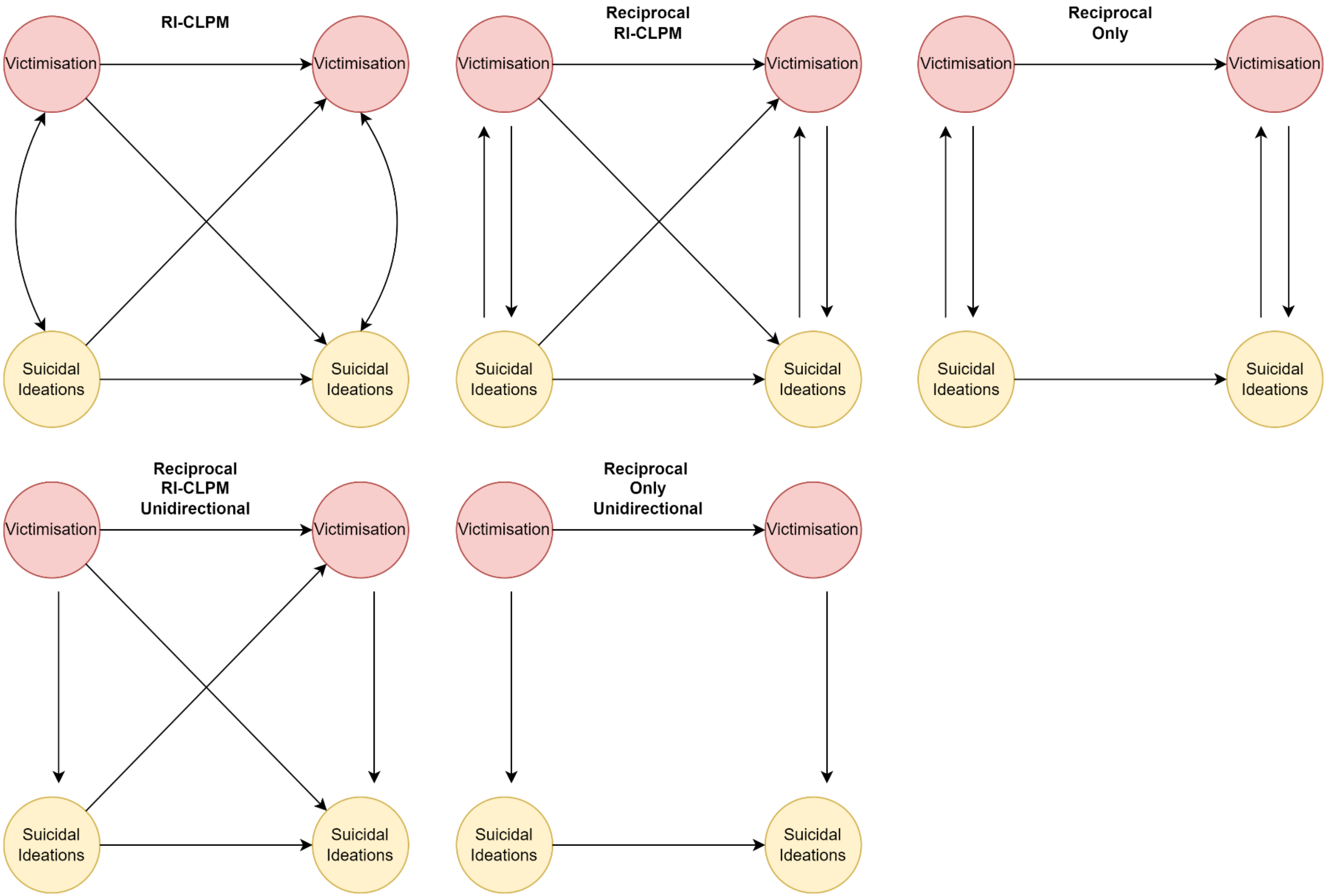
- Alternative model specification allowing for directional concurrent effects
- Requires some additional constraints for model identification
- Can be estimated in Mplus



In z-proso: associations between sexual bullying victimization and suicidal ideations

- Tested a series of RI-CLPMs including the Reciprocal RI-CLPM using different model specifications
- Sexual Bullying Victimisation at ages 13, 15, 17, 20 measured with reference frame of **past year**
- Suicidal Ideations at ages 13, 15, 17, 20 measured with reference frame of **past month**

z-proso
Zürcher Projekt zur sozialen Entwicklung
von der Kindheit ins Erwachsenenalter


RI-CLPM
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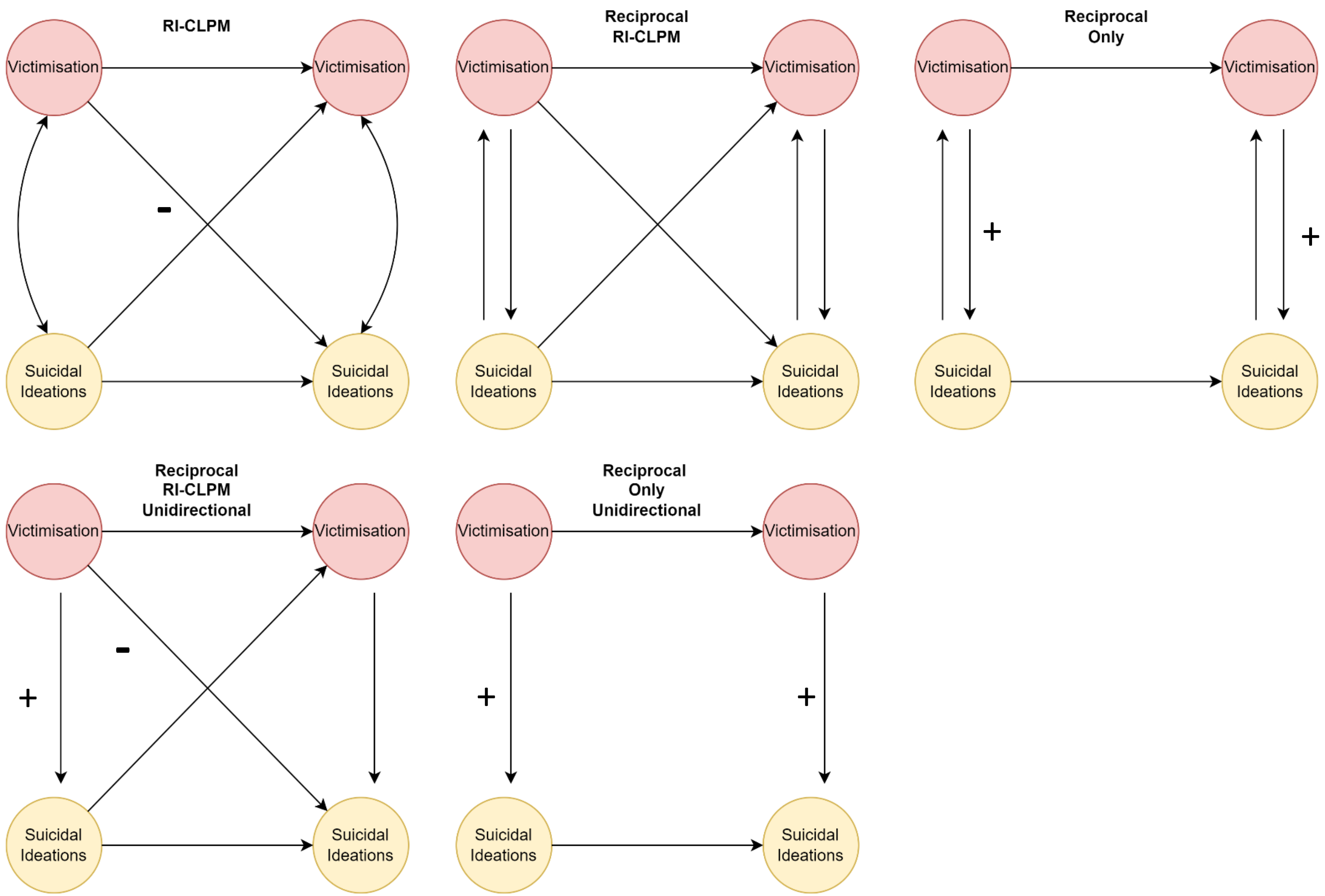
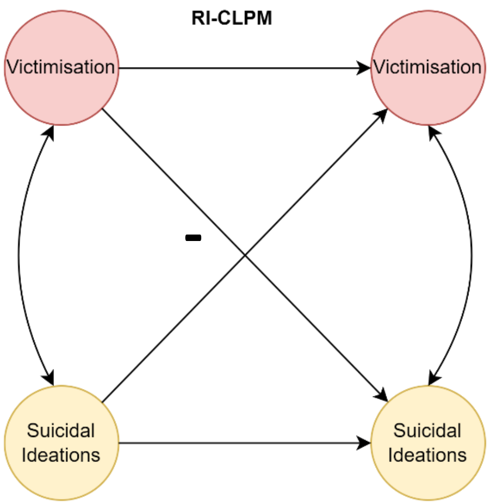
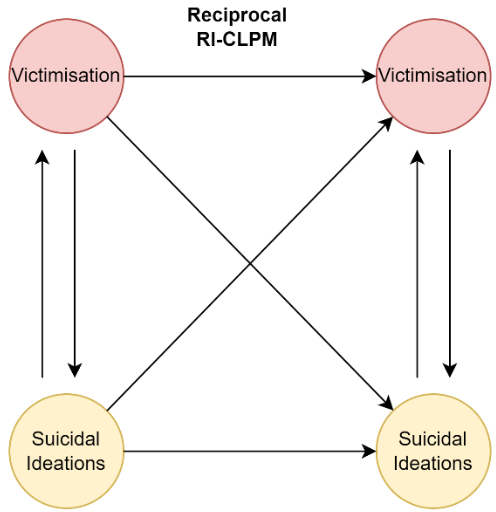
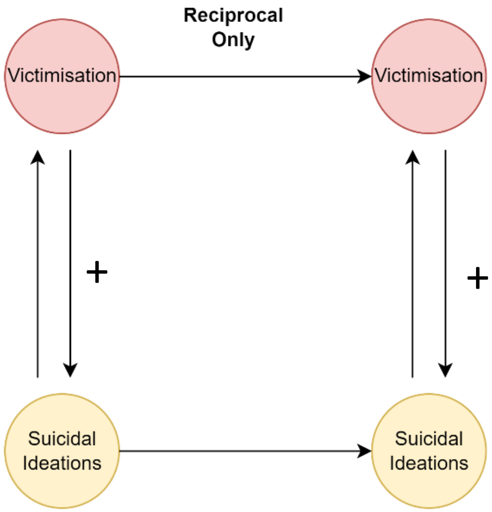


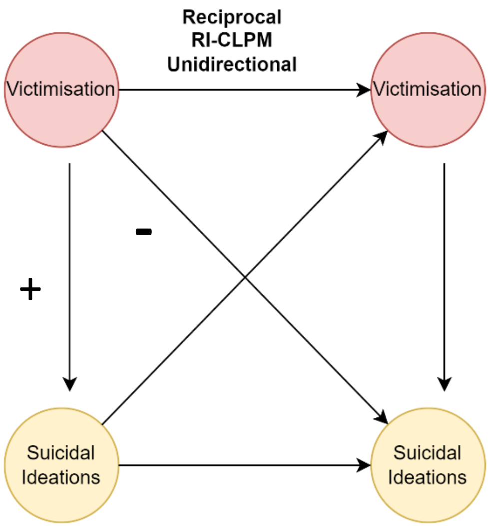
Model most closely aligned with data structure?

Best fit based on model parsimony and BIC









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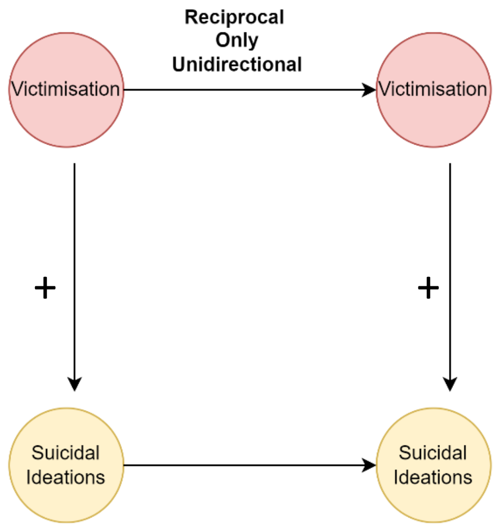

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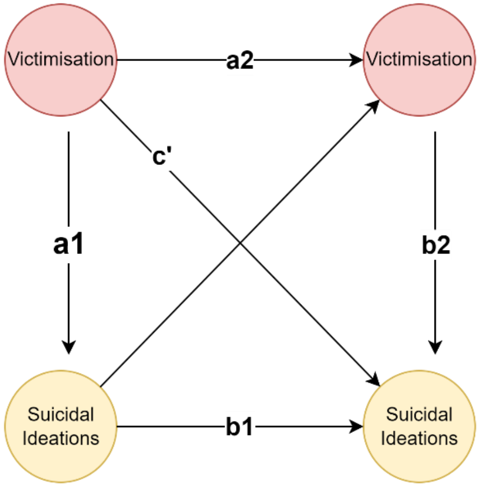


Possible mediation pathways capturing the total effect [(a1*b1) + (a2*b2) + c] of sexual bullying victimisation (SB) at age 17 on suicidal ideations (SI) at age 20.

Total Effect non-significant

RI-CLPMs are only as good as our theory, hypotheses and data. If our underlying theory is wrong or the data does not measure what was intended, the model will be wrong too.

"If you don't reveal some insights soon, I'm going to be forced to slice, dice, and drill!"

A single model is very unlikely to allow for causal conclusions

→ We need to draw conclusions based on robustness of effects across multiple models fit to multiple different datasets

If you want to know more…

Preprint: https://psyarxiv.com/h9eqf/

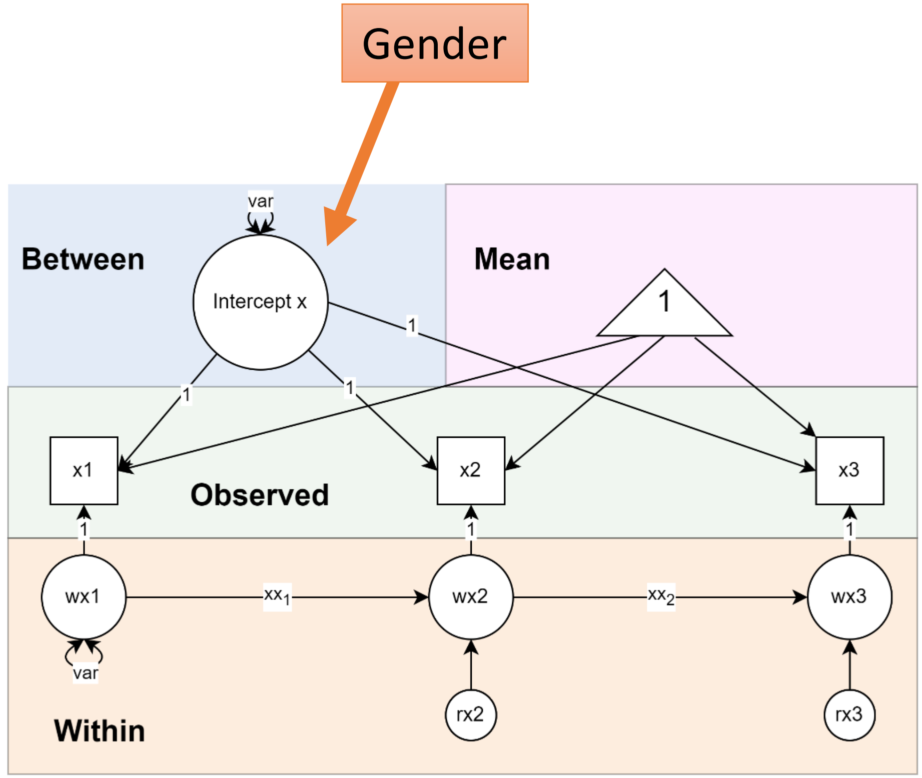
includes Mplus code for implementing the presented models

How well do RI-CLPMs control for unmeasured confounders?

- RI-CLPMs do a decent job controlling for stable between-person differences
  - BUT: even if the measure itself is stable (e.g. genes), that doesn't mean that their effect may not differ across time
    - the effect of gender may differ between early childhood and adolescence
  - if measured, can be incorporated as moderator or included as covariate at each time-point
- Not robust to unmeasured confounders!
  - Amplified for constructs changing over time
    - Within-person changes in medication intake may affect anxiety and sleep rather than there being a direct association between anxiety and sleep

Controlling for Confounders: Time-Invariant Predictors

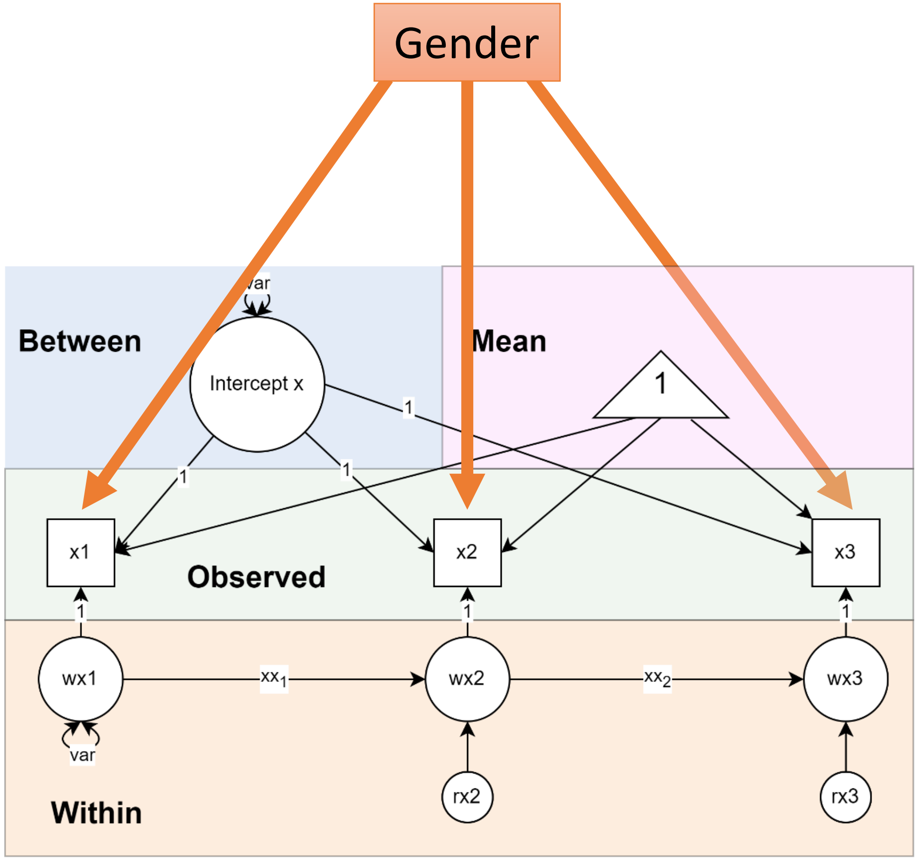
- We may be interested in whether time-invariant factors are associated with different components of our model
- E.g., gender or personality traits may be associated with between-person differences in anxiety (assumes stable effect)
  - Modelled as regressions predicting random intercepts in *lavaan* syntax
  - **RIx ~ gender**



(Mulder & Hamaker, 2021)

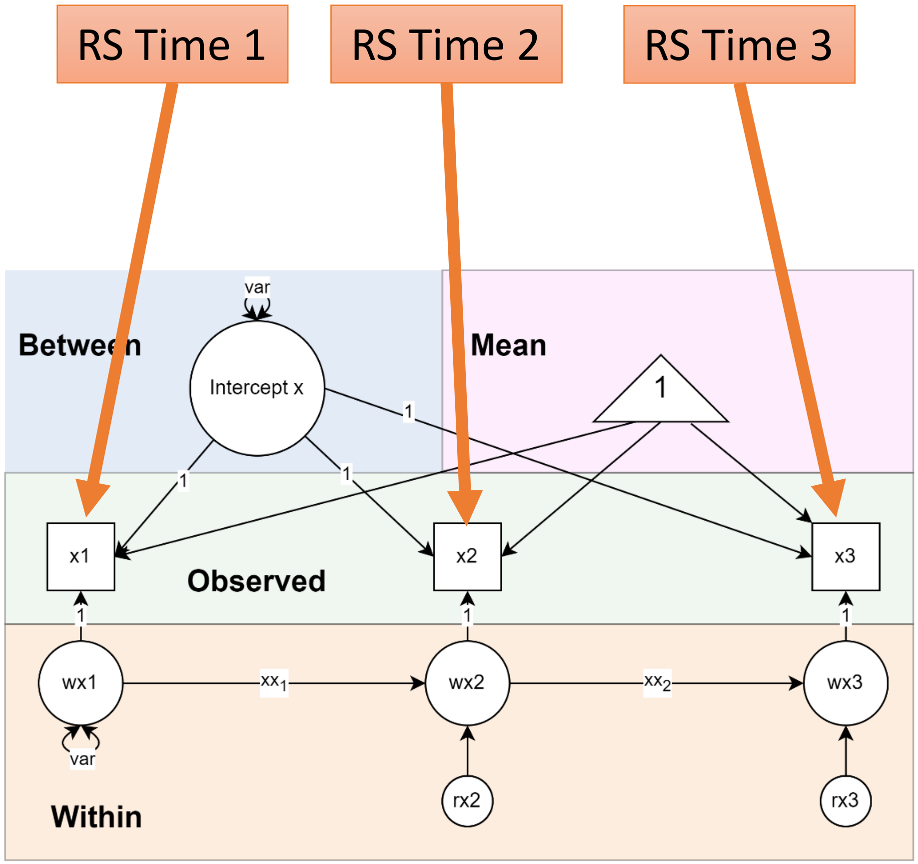
Controlling for Confounders: Time-Invariant Predictors

- We may be interested in whether time-invariant factors are associated with different components of our model
- They may also have different effects across time and thereby affect within-person components
  - Modelled as regressions predicting observed variables
  - **x1 ~ gender**
  - **x2 ~ gender**
  - **x3 ~ gender**



Controlling for Confounders: Time-Varying Predictors

- We may want to control for time-varying factors, e.g., relationship status
- In theory, they could just be modelled as an additional variable (and decomposed accordingly)
- In practice, that may make the model too complex
  - Modelled as regressions predicting observed variables
  - **x1 ~ gender**
  - **x2 ~ gender**
  - **x3 ~ gender**



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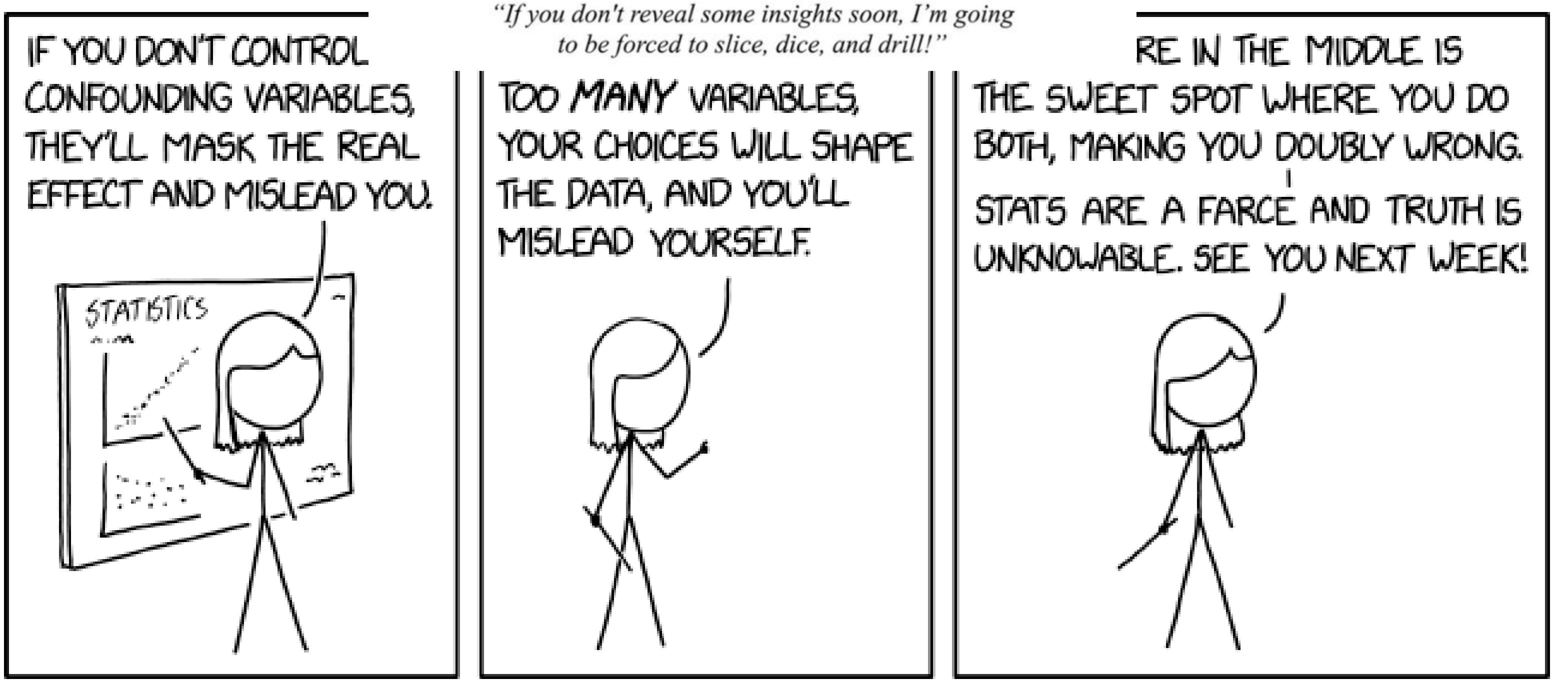

What pathways are the most plausible?

- Mediation from:
  - sleep → exercise → anxiety?
  - exercise → sleep → anxiety?
  - anxiety → sleep → exercise?
  - …
- Mediation or Moderation?