

On the Importance of Considering Concurrent Effects in Random-Intercept Cross-Lagged Panel Modelling: Example Analysis of Bullying and Internalising Problems

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ABSTRACT

Random-intercept cross-lagged panel models (RI-CLPMs) are increasingly used to investigate research questions focusing on how one variable at one time point affects another variable at the subsequent time point. Due to the implied temporal sequence of events in such research designs, interpretations of RI-CLPMs primarily focus on longitudinal cross-lagged paths while disregarding concurrent associations and modeling these only as residual covariances. However, this may cause biased cross-lagged effects. This may be especially so when data collected at the same time point refers to different reference timeframes, creating a temporal sequence of events for constructs measured concurrently. To examine this issue, we conducted a series of empirical analyses in which the impact of modeling or not modeling of directional within-time point associations may impact inferences drawn from RI-CLPMs using data from the longitudinal z-proso study. Results highlight that not considering directional concurrent effects may lead to biased cross-lagged effects. Thus, it is essential to carefully consider potential directional concurrent effects when choosing models to analyze directional associations between variables over time. If temporal sequences of concurrent effects cannot be clearly established, testing multiple models and drawing conclusions based on the robustness of effects across all models is recommended.

KEYWORDS

Random-intercept cross-lagged panel model; longitudinal modeling; concurrent effects; z-proso; bullying; internalizing problems

One of the most popular models for investigating longitudinal associations between multiple repeatedly measured variables is the Cross-Lagged Panel Model (CLPM) and its extension, the Random-Intercept CLPM (RI-CLPM) (Berry & Willoughby, 2017; Hamaker et al., 2015; Mund & Nestler, 2019). These models tend to be the method of choice when research questions focus on how one variable at one time point affects another variable at the subsequent time point. This, for example, allows for investigating whether aggressive behaviors are associated with subsequent increases in internalizing problems (Keskin et al., 2023; Murray et al., 2021). However, such models rarely consider potential directional pathways within the same measurement occasion even though reference frames for different measures frequently

operate across different time scales. In the following sections, we will first briefly describe the structure of (RI-)CLPMs and then discuss why ignoring such concurrent pathways may be problematic.

In their simplest form, cross-lagged panel models are made up of two constructs that are measured at two or more time points (Berry & Willoughby, 2017; Selig & Little, 2012). These time points are ideally spaced apart such that a temporal sequence of cause and effect can be established; that is variable x at time t is hypothesized to cause changes in variable y at time $t + 1$. If reciprocal cross-lagged associations are hypothesized, variable y at time t also causes changes in variable x at time $t + 1$. To adjust for autoregressive effects (i.e., changes in one variable caused by prior levels of that same variable), CLPMs additionally

model the associations between a variable at time t with the same variable at time $t+1$. Finally, CLPMs also typically include covariances to capture concurrent associations between variables x and y , which is their associations at the same time point (Berry & Willoughby, 2017). These associations are estimated for the residuals of variable x and y at time t ; that is after accounting for stability and cross-lagged effects. These residuals are assumed to be uncorrelated with the two predictors at the previous time point and are generally not a main focus in analyses involving variables measured at multiple time points (B. Muthén & Asparouhov, 2022, 2024). Extending the basic CLPM, RI-CLPMs additionally include random intercepts to disaggregate repeatedly measured observations into between- and within-person components. This is important since processes of primary interest to interventions tend to refer to within-person processes; that is how changes in one variable affect changes in another variable over time (Hamaker et al., 2015). The cross-lagged model is then fitted on the within-person component analogous to standard cross-lagged panel models.

Given the implied temporal sequence of cause and effect for cross-lagged paths, interpretations of (RI-)CLPMs predominantly focus on these longitudinal paths with little attention paid to within time point effects (B. Muthén & Asparouhov, 2022, 2024). This disregard for concurrent associations is partly due to the implicit assumption that variables measured at the same measurement occasion can only capture cross-sectional associations. However, within psychological and behavioral research, data collected at the same time point may not necessarily refer to the same reference timeframe. For example, questionnaire-based measures frequently use different reference timeframes when collecting information on a participant's behaviors or moods. Commonly, such questionnaires use longer timeframes to gain information on externally oriented behaviors or experiences that may only occur occasionally, such as engaging in criminal behaviors or experiencing victimization. On the other hand, they tend to use shorter timeframes to gain insights into internal states that are assumed to be more frequent or variable, such as symptoms of depression and anxiety. This is because survey participants may find it challenging to provide accurate responses regarding their long-term average levels of such internal states. (Igou et al., 2002; Winkielman et al., 1998). Thus, when analyzing for instance how external experiences asked about for the past year relate to internal states asked about for the past week, these

measures come with a plausible sequence of events. Specifically, the external experience is more likely to have preceded the internal state than vice versa. In such scenarios, bidirectional residual covariances do not necessarily accurately capture associations between variable x and variable y at the same time point.

A lack of attention to concurrent associations may not only obscure potentially interesting directional effects occurring within shorter timeframes but may additionally bias cross-lagged effects (B. Muthén & Asparouhov, 2022, 2024). This is because the common practice of estimating bidirectional covariances on the residuals of variable x and y at time $t+1$ presumes that these residuals are uncorrelated with the two predictors at the previous time point (x and y at time t). However, if the true data generating model is based on directional effects between variables within the same measurement occasion, this assumption is violated. Residuals become correlated with their predictors because each variable at time t is influenced by the other variable at time t (B. Muthén & Asparouhov, 2022, 2024). A handful of simulation studies have shown that assuming that there are no concurrent effects of x on y at time t may in fact result in bias in cross-lagged analyses. Cross-lagged effects may even point in the opposite direction than the true concurrent effects (Leszczensky & Wolbring, 2022; Vaisey & Miles, 2017).

In the literature, within time point associations are, however, rarely considered when investigating longitudinal associations. See for instance a RI-CLPM analysis of the longitudinal associations between criminal offending measured over the past year and mental health problems measured over the past week (Wiesner et al., 2023). Amidst various RI-CLPM analyses conducted using mismatched reference timeframes also resulting in counterintuitive findings (Zhu et al., 2022a, 2022b), this particular investigation suggests an unexpected linkage: an upsurge in criminal offenses over the past year appears to correspond with a subsequent reduction in mental health issues over the past week (Wiesner et al., 2023). Given that such counterintuitive findings may have wide-reaching implications, a careful setup and execution of RI-CLPM analyses, including the consideration of within time point associations in the context of the study's design and the used measures, is vital to ensure the robustness and validity of the result.

To more accurately capture concurrent associations in cross-lagged panel modeling, Muthén and Asparouhov (2022, 2024) recently proposed the reciprocal (RI-) CLPM as an alternative to classic (RI-)

CLPMs. Instead of modeling within time point associations only as residual covariances, the reciprocal RI-CLPM models these associations using reciprocal directional regression paths. Thus, it can give insights into directional links between two variables within the same time point. This aids the interpretation of concurrent effects and likely reduces potential bias in cross-lagged effects if the true data generating model is indeed based on directional concurrent effects. For a visualization of the reciprocal RI-CLPM as well as a comparison to the classic RI-CLPM, see Figure 1.

The current paper

In the following sections, we will first introduce the assumptions underlying the reciprocal RI-CLPM, detailing the restrictions required for this model to be identified. Then, to illustrate how different modeling choices for concurrent associations may impact empirical results, we will apply the reciprocal RI-CLPM as well as some of its variations to two sets of empirical data. Specifically, models will be applied to self-reported data on bullying victimization and internalizing problems measured repeatedly at ages 11, 13, 15, 17, and 20 as well as to self-reported data on suicidal ideations measured at ages 15, 17, and 20. In addition to estimating a classic RI-CLPM as well as a reciprocal RI-CLPM, we will also test the reciprocal only model and the reciprocal RI-CLPM with unidirectional rather than reciprocal concurrent paths.

Data used in the empirical analyses come from a sample of 1,522 youths taking part at least at one time point in the longitudinal Zurich Project on the Social Development from Childhood to Adulthood (Ribeaud et al., 2021). While bullying victimization was measured using a reference frame of the past year, internalizing problems and suicidal ideations were assessed using a reference frame of only the past month. This introduces a possible within-time point path from bullying victimization to internalizing problems and suicidal ideations. Consequently, it is important to consider a variety of different concurrent effects before estimating cross-lagged effects. Of note, given the partial overlap in reference frames, such a path is not the only possible path; thus, limiting conclusions drawn on true causal pathways. We provide annotated analysis code for on the Open Science Framework (OSF) to enable other researchers to implement these analyses for their own research questions in both Mplus and R.

The reciprocal random-intercept cross-lagged panel model

Recently proposed by Muthén and Asparouhov (2022, 2024) the reciprocal RI-CLPM very closely builds on the RI-CLPM. However, instead of including residual covariances to capture within-time point associations between two repeatedly measured variables, it includes reciprocal directional regression paths. These capture potential causal processes occurring within the same

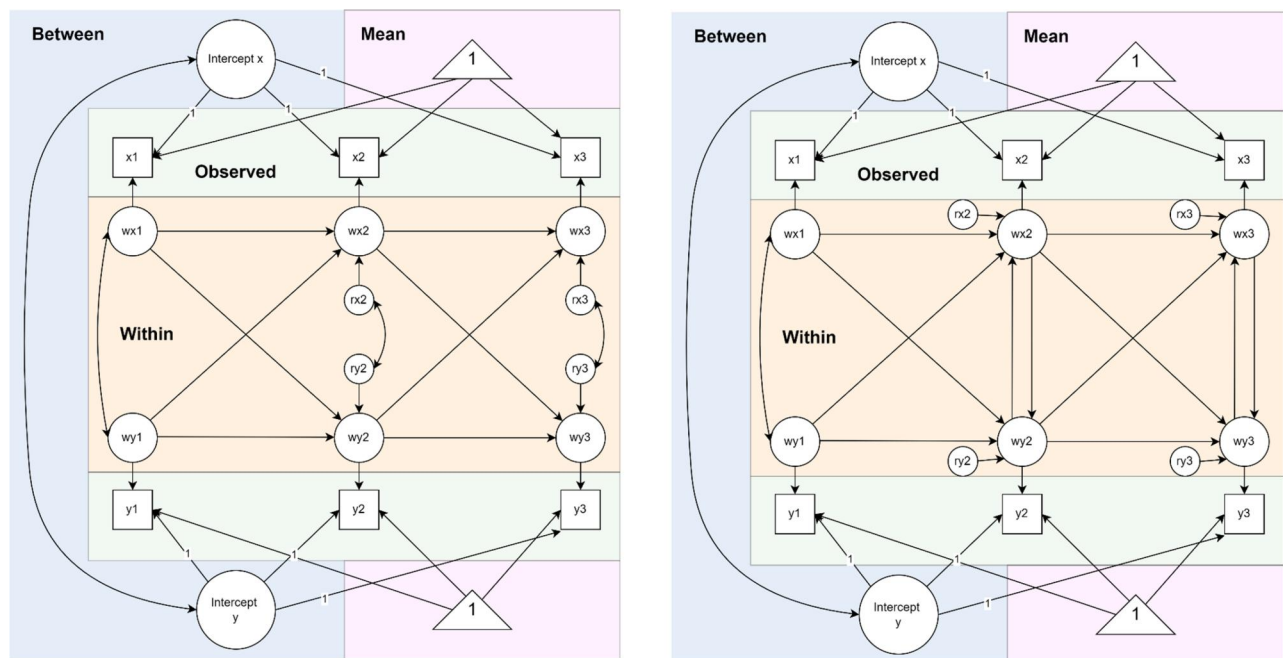


Figure 1. Illustrations of a 3-Wave Bivariate RI-CLPM (left) and 3-Wave Bivariate Reciprocal RI-CLPM (right). Circles represent latent variables, squares observed variables and triangles represent means. r = residual, w = within-person. Circles represent latent variables, squares observed variables and triangles represent means. r = residual, w = within-person.

measurement occasion. Importantly, the inclusion of reciprocal regression paths results in additional parameters (T-1 more parameters than the classic RI-CLPM). As such, additional model constraints need to be introduced to achieve equivalence to classic RI-CLPMs. With a minimum of two constructs measured over three time points, following Muthén and Asparouhov (2022, 2024), model identification can be achieved by placing equality constraints over time on some of the reciprocal effects. That is, the regression paths from variable x at time t to variable y at time t are constrained to be equal to the regression paths from x at $t+1$ to y at $t+1$. Further, the regression paths from y at time t to x at time t are constrained to be equal to the regression paths from y at time $t+1$ to x at time $t+1$. This specification essentially stipulates that there are no time-varying effects for these reciprocal effects; that is the concurrent effect of x on y at time 2 will be the same as the concurrent effect of x on y at time 3.

Given that the observations at the first time point are treated as exogenous in RI-CLPMs, equality constraints for reciprocal effects have to be set for the latter waves. For the first time point, as in RI-CLPMs, simple covariances should be estimated. To achieve model identification for models including more than three time points (T)-1 constraints are needed. For example, for four time points, three reciprocal effects need to be constrained to equality, whereas, for five time points, four reciprocal effects need to be equality constrained (e.g., reciprocal effects from x to y and y to x at times 2 and 3 as well as reciprocal effects from x to y and y to x at times 4 and 5) (B. Muthén & Asparouhov, 2022, 2024).

Importantly, even with time-invariance constraints introduced on the reciprocal effects (i.e., the directional within time point associations), the reciprocal RI-CLPM is not perfectly identified. In fact, the model has two solutions and may come with negative R-squared values. This type of innocuous model non-identification is similar to, for example, a 1-factor analysis in which factor loadings can be all negative or all positive. This is unlike a typical case of non-identification where there are infinitely many solutions. To find one acceptable solution rather than a dual solution and to avoid negative R-squared values, further restrictions need to be placed on the reciprocal structure. Muthén and Asparouhov (2022, 2024) suggest two types of possible restrictions:

- a. restricting reciprocal effects to both be either positive or negative which avoids dual solutions and negative R-squared values: $0 < \text{standardized regression coefficient } (r) \text{ } x \text{ on } y * r \text{ } y \text{ on } x < 1$
- b. restricting the *squared multiple correlation coefficient* $[(r \text{ } x \text{ on } y * r \text{ } y \text{ on } x)^2]$ to be less than 1 which avoids dual solutions but allows opposite signs of reciprocal effects and can result in negative R-squared values.

Given that under restriction (b), extra care needs to be taken to ensure that R-squared values are not negative, it is advisable to first test models using restriction (a). If one of the reciprocal effects is estimated as 0, suggesting that reciprocals are likely to have effects in opposite directions and thus, invalidating the assumption underlying restriction (a), restriction (b) may help achieve an admissible solution. For additional information, including technical details and model identification proofs, we refer the reader to B. Muthén and Asparouhov (2022, 2024).

Once restrictions are placed on the reciprocal RI-CLPM, the model has the exact same number of parameters and the same fit to the data as a classic RI-CLPM so the two models cannot be statistically distinguished. According to B. Muthén and Asparouhov (2022, 2024), this also means that a RI-CLPM showing evidence of cross-lagged effects cannot be used to rule out that the underlying data generating model was not based on reciprocal effects. Equally, a reciprocal RI-CLPM showing reciprocal effects cannot be used to rule out that the underlying data generating model was not based on cross-lagged effects only.

Two additional points need to be considered in the context of reciprocal RI-CLPMs. First, within reciprocal models, the effects captured by a cross-lagged path are not reflective of the total effect of a variable x at time t may have on variable y at time $t+1$. Specifically, the total effect of variable x at t on y at $t+1$ is made up of two mediation pathways plus the direct effect of x at t on y at $t+1$ (i.e., the cross-lagged effect, path c' in Figure 2). These mediation pathways include a pathway from x at t on y at t (i.e., the directional concurrent path at t , path **a1** in Figure 2) and from y at t to y at $t+1$ (i.e., the autoregressive effect for y , path **b1** in Figure 2). They further include a pathway from x at t on x at $t+1$ (i.e., the autoregressive effect for x , path **a2** in Figure 2) and from x at $t+1$ to y at $t+1$ (i.e., the directional concurrent path at $t+1$, path **b2** in Figure 2). Within reciprocal RI-CLPMs, these mediation pathways can be tested to gain insights into the overall effect a variable x may have on *another* variable y at the next time point $((a1*b1) + (a2*b2) + c')$. For example, this would allow for examining the overall effect of bullying at time t on internalizing problems at time

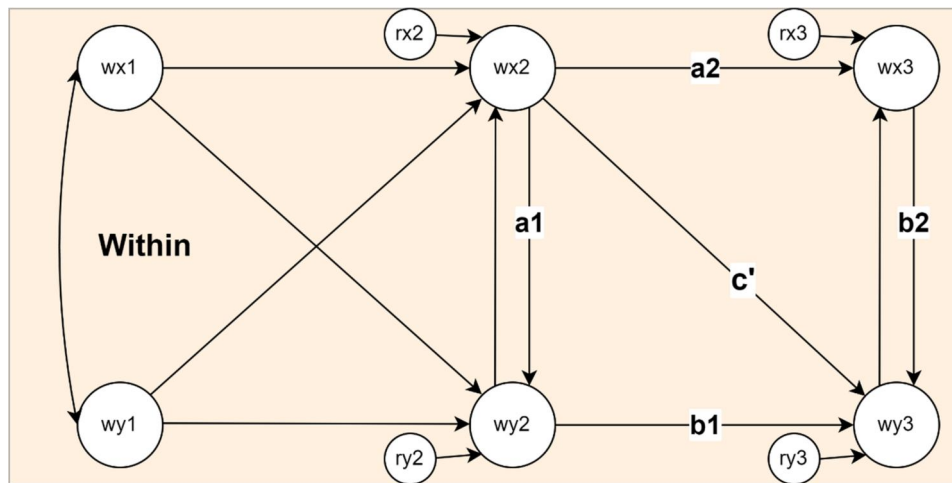


Figure 2. Mediation pathways for effect of x at t_2 on y at t_3 .

$t + 1$, accounting for direct pathways as well as indirect pathways *via* concurrent associations.

Second, it is not necessary to include bidirectional concurrent paths if there is reason to assume that only one within-time point association reflects a realistic pathway. For instance, in the context of different reference timeframes where one variable may be measured over the past month and the other measured in the moment (e.g., physical activity in the past month vs current heart rate), directional associations may only be plausible from the variable measured over the past month to the variable measured in the moment. A directional association in the other direction in this case may not be meaningful and the corresponding path does not necessarily need to be included. In such a unidirectional model, the aforementioned model constraint requirements are no longer necessary. Such a model is identified due to having less parameters than a bidirectional reciprocal model, allowing for additional flexibility. For instance, in such a model reciprocal effects could be allowed to vary across time.

In this context, it is also important to note that assumptions on the temporal sequence of variables measured at the same time points need to be made with caution, as there may be reporting biases that can influence the sequence of events. For instance, current depression could lead to over-reporting of external experiences, such as victimization over the past year. Thus, depression may partially be causally linked to their report on victimization even though their reference frame is temporally more recent. Also, in instances where reference frames overlap, internal states and external experiences could also have

occurred concurrently; thus, different reference frames do not guarantee a temporal sequence of events.

The decision of whether to include directional within time point paths, unidirectional or bidirectional, needs to be guided by properties of the measurement, the study's design, and the theories underpinning the constructs and research questions under investigation. When bidirectional paths are included, usually under the assumption that directionality between the constructs within the measurement occasion is not clear, results are most likely to only identify one directional path as being significant (B. Muthén & Asparouhov, 2022, 2024). As a next step, a unidirectional only model with its more straightforward interpretation should be considered as such a model is likely to fit better while also being more parsimonious. If models indeed suggest simultaneous bidirectional associations, this implies that the two constructs under investigation are in a state of equilibrium such that the dynamic interactions between them maintain a state of overall stability. This can, for example, be found in the econometrics literature in the context of supply and demand which need to balance each other out to achieve market equilibrium (Imbens, 2020).

Empirical example

We now present two empirical examples to illustrate how the estimation of concurrent directional effects compared to the estimation of concurrent residual covariances may influence inferences drawn from RI-CLPMs fit to longitudinal cohort study data.

A large amount of research has suggested that experiencing bullying victimization is associated with

internalizing problems, ranging from symptoms of anxiety or depression to increases in suicidal ideation (Averdijk et al., 2016; for meta-analyses, see Christina et al., 2021; and van Geel et al., 2022). However, to date, little research has examined their associations using study designs that appropriately disaggregate within- and between-person effects even though within-person effects are of primary interest to interventions (Hamaker et al., 2015). Only if changes in experiencing bullying victimization at the within-person level are in fact associated with changes in internalizing problems or suicidal ideations at the within-person level are interventions targeting bullying likely to have an impact on subsequent emotional difficulties. For a thorough literature review motivating research into the links between bullying victimization and internalizing problems, please refer to Zhu et al. (2022a, 2022b).

Using the same data as the examples used in the current study, a handful of studies have investigated within-person associations between (sexual) bullying victimization, internalizing problems, and suicidal ideations. Interestingly, these previous analyses using RI-CLPMs led to some unexpected findings, suggesting for instance that sexual bullying victimization is in fact associated with a reduction rather than an increase in suicidal ideations at the within-person level (Zhu et al., 2022a, 2022b). These surprising findings warrant further investigation. One possible reason could be that these findings reflect the aforementioned issues of mismatched reference timeframes for variables assumed to be only reflecting cross-sectional associations. In fact, within z-proso, suicidal ideations and internalizing problems were measured using a reference timeframe of the past month whereas experiences of (sexual) bullying victimization were measured using a reference timeframe of the past year. This implies an increased likelihood for directional effects from (sexual) bullying to internalizing problems captured within the same measurement occasion. Of note, given the overlap in reference frames for the period of 1 month, a directional effect from internalizing problems to sexual bullying may still be possible, however less likely.

In the following analyses, we will examine the associations between bullying victimization and internalizing problems across early to middle adolescence as well as between sexual bullying victimization and suicidal ideations across middle to late adolescence using a series of structural equation models including the above-described reciprocal RI-CLPM. This will give insights into how different choices for modeling

concurrent associations may impact model interpretation and results.

Participants

The participants in the current study were 1,522 (52% male) young people who participated in the Zurich Project on the Social Development from Childhood to Adulthood (z-proso). Z-proso is a longitudinal cohort study that has been following the lives of an initial target sample of 1,675 children from primary school entry at age 7 up until age 24 with data collection still ongoing. To be representative of the underlying same-age population, participants were initially recruited using a stratified sampling design from 56 primary schools in Zurich. At age 11, participants moved into different secondary schools. Analyses of potential school level clustering effects suggest that these effects are negligible (Intra Class Correlation Coefficients < 0.05), thus, nesting of students within school is not controlled for in the analyses. The current sample consisted of those 1,522 participants who contributed data at least at one of the age 11, 13, 15, 17, and 20 waves at which waves the variables of interest to the current study were measured.

For detailed information on the z-proso study, including information on attrition and detailed demographic characteristics, see (Eisner et al., 2019; Ribeaud et al., 2022). Ethical approval for the z-proso study was granted by the Ethics Committee from the Faculty of Arts and Social Sciences of the University of Zurich. Active informed consent for participating in the study was given by the participants' parents up until age 12 and by the participants themselves from age 13 onwards. At ages 13 and 15, parents could opt their children out of the study (passive informed consent).

Measures

Internalizing problems were assessed at ages 11, 13, 15, and 17 using adapted self-report versions of the Social Behavior Questionnaire (SBQ) (Tremblay et al., 1991). The SBQ measures youths' psycho-social development across five domains including anxiety/depression, aggression, non-aggressive externalizing problems, ADHD symptoms, and prosocial behavior. Responses for the SBQ were recorded on a five-point scale ranging from *never* to *very often*. At the age 11 to 17 waves, the SBQ included 4 items on anxiety and 4 items on depression that were summed up to form a composite score with higher scores indicating more internalizing problems. The psychometric properties of the SBQ in the current study sample have

been analyzed extensively elsewhere (Murray et al., 2019), supporting its reliability, factorial validity, and measurement invariance up to the metric level. Importantly, for items relating to anxiety and depression, participants were asked to respond regarding their experience of those symptoms over the **past month**.

At ages 15, 17, and 20, participants were further asked how often they had thought about suicide (five-point scale, never to very often). Prior research using such a one-item measure of young people's suicidal ideation (Marschall-Lévesque et al., 2017; Perret et al., 2020) has suggested that these can serve as a brief and valid approach for screening. Further, previous research has used this item in the current sample and supported its validity (Steinhoff et al., 2021). As for internalizing problem items, this item was asked referring to suicidal ideations over the **past month**.

Bullying victimization was measured at ages 11, 13, 15, 17, and 20 using the Zurich Brief Bullying Scales (ZBBS) (Murray et al., 2021). The ZBBS is a self-report questionnaire that includes one item each on social exclusion, physical aggression, verbal aggression and property destruction (e.g., *Have you been purposely ignored or excluded*). Items were scored on a 6-point scale (*never to (almost) every day*) and were summed up to derive a composite score with higher scores indicating more bullying victimization. At ages 13, 15, 17, and 20, the ZBBS further included one item on sexual bullying victimization (*Have you been sexually harassed (e.g., hit on, groped)*, measured on the same scale as the general bullying items.

Psychometric analyses of the ZBBS in the study sample have suggested reasonably good psychometric properties (Murray et al., 2021). However, given that the sexual victimization item showed a low loading on the general victimization scale in Murray et al. (2021), it was not included in the overall bullying scale but analyzed as a single item measure of sexual bullying victimization (see also, Zhu et al., 2022a). Importantly, items were asked using a reference timeframe of the past year, i.e., indicating how often in the **past year** participants experienced (sexual) bullying victimization.

Statistical analysis

To test how the estimation of concurrent associations using directional paths affects cross-lagged parameters and to illustrate differences in the interpretation of results, we fit a series of structural equation models testing the associations between bullying victimization and internalizing problems across ages 11 to 17. Some of the planned analyses involve time-invariance restriction which presupposes equal measurement occasions. Therefore, we only included internalizing problems and bullying victimization across ages 11 to 17 in this model even though data for these constructs were also available at age 20.

We started our analyses with a classic RI-CLPM and tested two versions of this model, one freely estimating all paths and one constraining cross-lagged effects to be equal across time (Figure 3c). We then

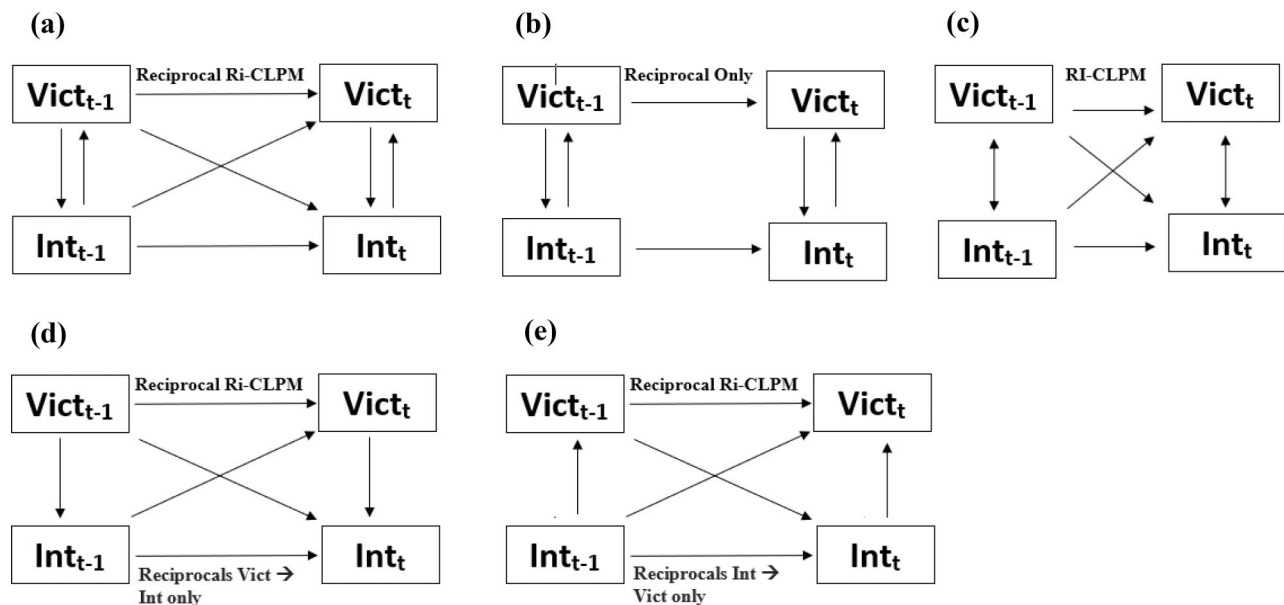


Figure 3. Illustration of the series of structural equation models fit to data on internalizing problems (Int) and bullying victimization (Vict). Models are fit with equality constraints over time placed on the cross-lagged and/or reciprocal structure as well as with paths estimated freely. Figure (a) shows a reciprocal RI-CLPM, Figure (b) shows a reciprocal only model, Figure (c) shows a classic RI-CLPM, Figure (d) shows a reciprocal RI-CLPM with only a unidirectional concurrent path from bullying victimization to internalizing problems, and Figure (e) shows a reciprocal RI-CLPM with only a unidirectional concurrent path from internalizing problems to bullying victimization.

estimated a reciprocal only model; that is a model that did not include any cross-lagged effects but only concurrent paths. We fit this model once with time-varying reciprocal effects and once with reciprocal effects constrained to be the same within all time points (Figure 3b). Further, we tested a reciprocal RI-CLPM, starting off with a fully constrained model; that is both reciprocal effects and cross-lagged paths constrained to be equal within/across time, respectively (Figure 3a). We then relaxed these constraints for the cross-lagged paths but kept reciprocal effects constrained to be time-invariant. This is necessary for model identification. Next, we dropped one of the reciprocal paths to estimate a model containing only a unidirectional concurrent path from bullying victimization to internalizing problems (Figure 3d). This most closely (although not perfectly given the overlap in reference frames) aligns with the underlying data structure given the different reference frames (**past year** vs **past month**). In a second model, we only included unidirectional concurrent paths from internalizing problems to bullying victimization (Figure 3e). Both of these RI-CLPMs with unidirectional concurrent paths were again estimated twice, once with all paths allowed to vary freely, and once with both reciprocal effects and cross-lagged paths set to be equal within/across time.

For the analysis of the associations between sexual bullying victimization and suicidal ideations, we fitted the same models as for internalizing problems. Given the unequal spacing of measurement occasions (15, 17, 20), however, we did not fit those models that involved time-invariance constraints for the cross-lagged paths. Invariance constraints for reciprocal effects were deemed to be unproblematic since these are added within-time points and thus only require these variables to be measured using the same reference timeframes (i.e., past month or past year) irrespective of how frequently they were measured across time.

All our models were estimated using full information maximum likelihood estimation (FIML) (Enders, 2001). With a robust estimator (MLR) in Mplus version 8.8 (L. K. Muthén & Muthén, 1998). To assess, statistical significance of indirect effects (mediation pathways) in reciprocal RI-CLPMs which show an asymmetric sampling distribution, we further computed bootstrapped 95% confidence intervals to assess statistical significance using standard maximum likelihood estimation. We use the following model fit indices as indicators of acceptable model fit: Tucker Lewis Index (TLI): >0.90 ; Comparative Fit Index (CFI):

>0.90 ; Root Mean Squared Error of Approximation (RMSEA): <0.05 ; Standardized Root Mean Square Residual (SRMR): <0.05 (Hair et al., 2010). For model comparisons, we evaluate the Bayesian Information Criterion (BIC) and favor the model with the smaller BIC. If the BIC does not clearly favor one model over the other ($BIC\Delta < 10$), we further evaluate model parsimony and favor the model with fewer parameters.

Mplus code and full model results are available on the OSF as well as in appendices 1-19: https://osf.io/vt6bw/?view_only=50cb0ad3eff3445a9ebf74c8e9ef52e0. Model syntax for implementing reciprocal RI-CLPMs in the open source software R (R Core Team, 2017) is available in appendix 20.

Results

Bullying victimization and internalizing problems

Model fit

Overall, model fits were relatively similar across models with all models showing acceptable CFI, TLI, RMSEA, and SRMR values. The following models had the lowest BIC: the reciprocal RI-CLPM with invariant cross-lagged and invariant reciprocal effects (Table 1 #7), the reciprocal RI-CLPM with invariant cross-lagged and invariant unidirectional reciprocal effects from victimization to internalizing (Table 1 #6), the reciprocal only model (Table 1 #3), and the RI-CLPM with invariant cross-lagged effects (Table 1 #2). These models showed BICs differing by only ~ 2 points. Of note, generally models with invariance constraints introduced were favored over models with paths estimated freely, likely due to the reduced model complexity.

As the BIC did not clearly favor one model, we proceeded to evaluate model parsimony. The reciprocal RI-CLPM with invariant cross-lagged and invariant *unidirectional* reciprocal effects from victimization to internalizing had the lowest number of parameters out of the models with the lowest BIC. This suggests that this model may be preferable over the others. Given the implied temporal sequence in items measuring victimization and internalizing problems (**past year** vs **past month**), this model is also the model that may be preferred on theoretical grounds. Specifically, the *unidirectional* within-time point regression path from victimization to internalizing captures this sequence more accurately than a simple *covariance* as in the classic RI-CLPM or *bidirectional* paths also modeling directional effects from internalizing to victimization. In line with this, the equivalent model in terms of number of parameters—that is the reciprocal RI-CLPM with

Table 1. Summary of models fit for associations between bullying victimization (Vict) and internalizing problems (Int) across ages 11, 13, 15, and 17.

# Model Specification	#par	LogL	BIC	CFI	TLI	RMSEA	SRMR	Sig. CL-Effects	Sig. Reciprocal Effects
1. RI-CLPM	35	-10070.051	20396.575	.993	.978	.032	.020	Age 11 Vict → +Int Age 13, 15 Int → +Vict Vict → +Int	-
2. RI-CLPM Invariant X-lags	31	-10075.452	20378.064	.990	.979	.031	.025	Age 11 Vict → +Int Age 13, 15 Int → +Vict Vict → +Int	-
3. Reciprocal Only	31	-10071.532	20377.553	.993	.983	.028	.025	Age 11 Vict → +Int Age 13, 15 Int → +Vict Vict → +Int	Age 13 Vict → +Int Age 15, 17 Int → +Vict
4. Reciprocal Only Invariant Reciprocal Effects	28	-10089.610	20384.399	.978	.962	.042	.039	Age 11 Vict → +Int Age 13, 15 Int → +Vict Vict → +Int	Age 13 Vict → +Int Age 15, 17 Int → +Vict
5. Reciprocal RI-CLPM Invariant Reciprocal Effects	34	-10070.781	20390.706	.993	.981	.030	.022	Age 11 Vict → +Int Age 13, 15 Int → +Vict Vict → +Int	Age 13 Vict → +Int Age 15, 17 Int → +Vict
6. Reciprocal RI-CLPM Invariant X-lags and Invariant Reciprocal Effects	30	-10078.100	20376.033	.989	.977	.032	.027	Age 11 Vict → +Int Age 13, 15 Int → +Vict Vict → +Int	Age 13 Vict → +Int Age 15, 17 Int → +Vict
7. Reciprocal RI-CLPM Invariant X-lags and Invariant Reciprocal Effects Vict → Int only	29	-10082.103	20376.712	.985	.973	.036	.031	Age 11 Vict → +Int Age 13, 15 Int → +Vict Vict → +Int	Age 13 Vict → +Int Age 15, 17 Int → +Vict
8. Reciprocal RI-CLPM and Reciprocal Effects Vict → Int only	35	-10070.051	20396.575	.993	.978	.032	.020	Age 11 Vict → +Int Age 13, 15 Int → +Vict Vict → +Int	Age 13 Vict → +Int Age 15, 17 Int → +Vict
9. Reciprocal RI-CLPM Invariant X-lags and Invariant Reciprocal Effects Int → Vict only	29	-10105.921	20424.347	.964	.932	.056	.045	Age 11 Vict → +Int Age 13, 15 Int → +Vict Vict → +Int	Age 13 Vict → +Int Age 15, 17 Int → +Vict
10. Reciprocal RI-CLPM and Reciprocal Effects Int → Vict only	35	-10070.051	20396.575	.993	.978	.032	.020	Age 11 Vict → +Int Age 13, 15 Int → +Vict Vict → +Int	Age 13 Vict → +Int Age 15, 17 Int → +Vict

Note. The best fitting model based on BIC and model parsimony is model 7 which has approximately the same BIC as models 2, 3, and 6 but a lower number of parameters.

invariant cross-lagged and invariant *unidirectional* reciprocal effects from internalizing to victimization—showed the worst model fit based on BIC out of all models. Considering that this model included a directional path from internalizing to victimization within time points, the worse model fit is not unexpected. The reference frame for these items would suggest that this is an unlikely causal chain. For model fit statistics of all models, see Table 1.

Comparison of findings across all models

When looking at the observed effects in the different models, the following main findings emerged: First, cross-lagged effects from internalizing problems to bullying victimization were relatively consistent across all models. In contrast, cross-lagged effects from bullying victimization to internalizing problems only emerged in the RI-CLPMs without reciprocal effects and for a single time point in two of the models that also included reciprocals. When looking at the reciprocal effects capturing directional within-time point associations, the opposite finding emerged. The effect of bullying victimization on increases in internalizing problems was more robustly observed than the effect of internalizing problems on increases in bullying victimization. In fact, the latter effect showed significant signs in the opposite directions in some of the models. Taken together, these results suggest that the directional links from internalizing problems to experiencing bullying victimization may play out over longer periods and may indeed be accurately captured by cross-lagged paths. The directional links from victimization to internalizing problems, however, are likely observed due to short-term processes, capturing the sequence of events also implied by the different reference time frames over which these constructs were captured within the same time point.

In terms of between-person effects, these remained consistent across all models, indicating a moderate correlation between internalizing problems and bullying victimization at this level. This implies that individuals with high scores in bullying victimization tend to also exhibit higher scores in internalizing problems, compared to those with low bullying victimization scores, and vice versa. Full results for all models are available in appendices 1 to 10 and on OSF: https://osf.io/vt6bw/?view_only=50cb0ad3eff3445a9ebf74c8e9ef52e0.

Results for model favored based on model fit and parsimony

Across all models, the RI-CLPM with invariant cross-lagged and invariant unidirectional reciprocal effects

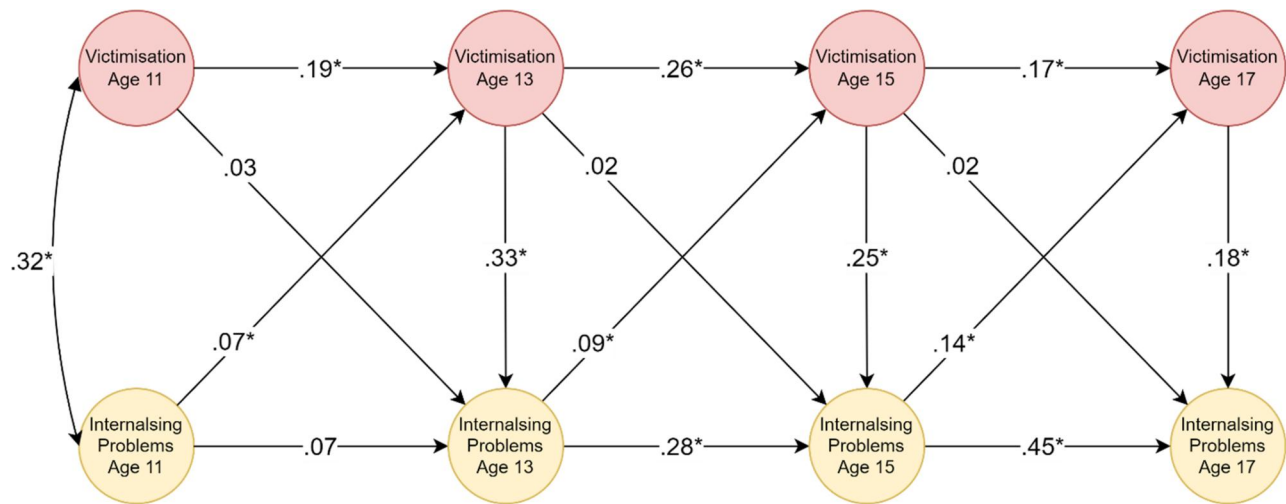


Figure 4. Standardized regression coefficients for the best fitting model for bullying victimization and internalizing problems. Random intercepts are omitted for clarity.

from victimization to internalizing problems showed the best model fit (CFI = 0.985; TLI = 0.973; RMSEA = 0.036; SRMR = 0.031) in conjunction with model parsimony (29 parameters) and theoretical plausibility and is therefore favored for interpretation. This model suggested that internalizing problems are associated with increases in bullying victimization across measurement occasions. In contrast, victimization is associated with increases in internalizing problems within measurement occasions, aligning with results also emerging across all models. For a summary of significant cross-lagged and reciprocal effects, see Figure 4 as well as Table 2 for full result.

Sexual bullying victimization and suicidal ideations

Model fit

As for the model including victimization and internalizing problems, model fit of all tested models were generally good. The reciprocal only model (Table 3 #2), demonstrated the most favorable model fit, as it had the lowest BIC among all models. Notably, this model revealed a directional effect from suicidal ideation to an increase in sexual bullying victimization, which is a concurrent effect that conflicts with the reference timeframes used to measure sexual bullying and suicidal ideation. Nevertheless, since the reference frames for both constructs overlapped by a month, this path remains plausible albeit less likely. We also more closely examined the reciprocal only model including a directional path from sexual bullying victimization to suicidal ideation only (Table 1 #4). This model aligns more closely with the implied direction of effects given the variables' reference timeframes. It

showed the second lowest, and very similar BIC to the model including both reciprocal effects and was favored also based on model parsimony. In this model, the directional effect from sexual bullying victimization to increases in suicidal ideations was significant, highlighting how sensitive these models may be to specifications that may not accurately reflect the temporal sequence over which the data was collected. Notably, models including cross-lagged effects fit worse than those just including reciprocal effects. For model fit statistics of all models, see Table 3.

Comparison of findings across all models

When looking at the general pattern of results across all models, of note was a relatively consistent cross-lagged effect of experiencing sexual bullying victimization leading to a reduction in suicidal ideations over the age 17 to 20 lag. This effect has been reported in previous publications using a classic RI-CLPM (Zhu et al., 2022b, 2022a), but is highly counterintuitive and would, if reflecting a real effect, have highly problematic implications. This effect consequently warrants further examination.

Based on the conducted analyses, two findings are noteworthy. First, in the most complex model which estimates all possible cross-lagged and reciprocal effects (the reciprocal RI-CLPM with invariant reciprocal effects), this effect was not significant. Secondly, within reciprocal RI-CLPMs, it is important to consider that the cross-lagged effect of sexual bullying at age 17 on reduced suicidal ideation at age 20 only captures part of the effect of sexual bullying victimization reported at age 17 on suicidal ideation at age 20 rather than the total effect. The total effect also includes a pathway *via* suicidal ideation at age 17 (i.e.,

Table 2. Parameter estimates for RI-CLPM with invariant cross-lagged and invariant unidirectional reciprocal effects from victimization to internalizing problems.

	Estimate	Std. estimate	Standard error	P-value
Within-person autoregressive effects				
Age 13 internalizing on age 11 internalizing	.071	.067	.071	.352
Age 15 internalizing on age 13 internalizing	.330	.283	.052	<.001*
Age 17 internalizing on age 15 internalizing	.475	.448	.036	<.001*
Age 13 victimization on age 11 victimization	.179	.191	.042	<.001*
Age 15 victimization on age 13 victimization	.225	.261	.049	<.001*
Age 17 victimization on age 15 victimization	.128	.167	.067	.012*
Within-person cross-lagged effects				
Age 13 internalizing on age 11 victimization	.024	.030	.030	.315
Age 15 internalizing on age 13 victimization	.024	.024	.024	.313
Age 17 internalizing on age 15 victimization	.024	.019	.019	.309
Age 13 victimization on age 11 internalizing	.091	.073	.020	<.001*
Age 15 victimization on age 13 internalizing	.091	.091	.026	<.001*
Age 17 victimization on age 15 internalizing	.091	.138	.040	.001*
Within-person reciprocal effects				
Age 13 internalizing on age 13 victimization	.288	.333	.036	<.001*
Age 15 internalizing on age 15 victimization	.288	.246	.024	<.001*
Age 17 internalizing on age 17 victimization	.288	.178	.019	<.001*
Within-person covariances				
Age 11 internalizing with age 11 victimization	.124	.321	.039	<.001*
Within-person total indirect effects				
Age 15 internalizing on age 13 victimization <i>via</i> age 13 internalizing and age 15 victimization	.160	NA	Ustd. SE: .023	<.001*
Age 17 internalizing on age 15 victimization <i>via</i> age 15 internalizing and age 17 victimization	.174	NA	Ustd. SE: .030	<.001*
Within-person total effects				
Direct effect of age 15 internalizing on age 13 victimization + effect of age 13 victimization <i>via</i> age 13 internalizing and age 15 victimization	.184	NA	Ustd. SE: .022	<.001*
Direct effect of age 17 internalizing on age 15 victimization + effect of age 15 victimization <i>via</i> age 15 internalizing and age 17 victimization	.198	NA	Ustd. SE: .030	<.001*
Between-person covariances				
Random intercept internalizing with random intercept victimization	.050	.353	.063	<.001*

Note. For total effects, standardized estimates are not available. *significant at $p < 0.05$.

Table 3. Summary of models fit for associations between sexual bullying victimization and suicidal ideations across ages 15, 17, and 20.

	#par	LogL	BIC	CFI	TLI	RMSEA	SRMR	Sig. CL-Effects	Sig. Reciprocal Effects
1. RI-CLPM	26	-8943.982	18077.494	.997	.952	.033	.011	Age 17 SB → -SI	NA
2. Reciprocal Only	18	-8946.008	18066.967	.994	.969	.026	.014	NA	Age 20 SI → +SB Age 17 SB → -SI SI → +SB
3. Reciprocal Only Invariant Reciprocal Effects	22	-8947.030	18054.431	.996	.988	.016	.016	NA	SB → +SI
4. Reciprocal Only Invariant Reciprocal Effects SB → SI only	21	-8952.876	18058.834	.980	.950	.033	.026	NA	SB → +SI
5. Reciprocal RI-CLPM Invariant Reciprocal Effects	26	-8943.982	18077.494	.997	.952	.033	.011	—	—
6. Reciprocal RI-CLPM and Reciprocal Effects SB → SI only	26	-8943.982	18077.494	.997	.952	.033	.011	Age 17 SB → -SI	Age 17 SB → +SI
7. Reciprocal RI-CLPM and Invariant Reciprocal Effects SB → SI only	25	-8945.400	18073.041	.995	.965	.028	.014	Age 17 SB → -SI	—
8. Reciprocal RI-CLPM and Reciprocal Effects SI → SB only	26	-8943.982	18077.494	.997	.952	.033	.011	Age 17 SB → -SI	—
9. Reciprocal RI-CLPM and Invariant Reciprocal Effects SI → SB only	25	-8944.793	18071.827	.997	.980	.021	.013	Age 17 SB → -SI	—

Note. The best fitting model based on BIC, model parsimony, and theoretical plausibility of pathways is model 4.

sexual bullying reported at age 17 experienced over the previous year → suicidal ideation at age 17 experienced over the previous month → suicidal ideation at age 20) and a pathway *via* sexual bullying at age 20

(i.e., sexual bullying reported at age 17 → sexual bullying reported at age 20 → suicidal ideation at age 20). That is, the autoregressive effects of suicidal ideations and sexual bullying as well as the concurrent

effects from sexual bullying to suicidal ideation capture part of the overall effect of sexual bullying at age 17 on suicidal ideation at age 20. This can be analyzed as a simple mediation model, see Figure 5.

Across most of the considered models, the total effect (calculated as $a1*b1 + a2*b2 + c'$), assessed for significance using bootstrapped 95% confidence intervals, was not significant. Thus, it seems as if the indirect and direct pathways cancel each other out. This can most easily be seen for the reciprocal RI-CLPM model with a unidirectional path from sexual bullying to suicidal ideations only (aligning with the implied temporal sequence due to differences in reference timeframes). This model indeed suggested a negative cross-lagged effect but a positive concurrent effect of sexual bullying victimization on suicidal ideations with the total effect of sexual bullying victimization on suicidal ideations not being significant.

With regards to between-person effects, these were essentially the same across all models. This indicates that suicidal ideations and sexual bullying

victimization are moderately correlated at the between-person level. This suggests that those with high scores on sexual bullying victimization are likely to also have higher scores on suicidal ideations compared to those who are low on sexual bullying victimization and vice versa. See appendices 11 to 19 or OSF for full model results: https://osf.io/vt6bw/?view_only=50cb0ad3eff3445a9ebf74c8e9ef52e0.

Results for model favored based on model fit and parsimony

Based on model parsimony (21 parameters), model fit (CFI = 0.980; TLI = 0.950; RMSEA = 0.033; SRMR = 0.026) and theoretical plausibility, we favored the reciprocal only model including a directional path from sexual bullying victimization to suicidal ideation only for interpretation. This model suggested that sexual bullying victimization was associated with a small increase in suicidal ideations within the same measurement occasion. For a summary of significant reciprocal effects, see Figure 6 as well as Table 4 for full results.

Discussion

The purpose of this study was to emphasize the importance of considering concurrent associations in random intercept cross-lagged panel modeling (RI-CLPM). We argued that neglecting concurrent associations in classic RI-CLPMs could be particularly problematic when variables measured at the same measurement occasion refer to different reference timeframes. Specifically, classic RI-CLPMs may erroneously suggest significant cross-lagged effects across

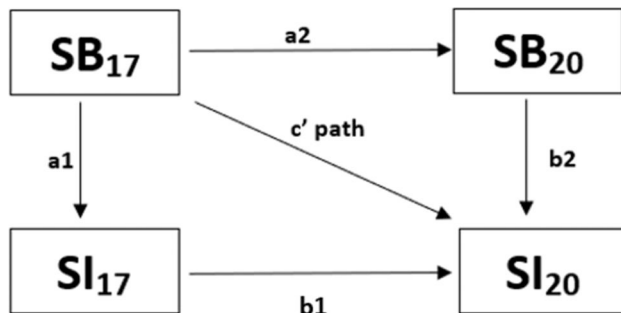


Figure 5. Possible mediation pathways capturing the total effect $[(a1*b1) + (a2*b2) + c']$ of sexual bullying victimization (SB) at age 17 on suicidal ideations (SI) at age 20.

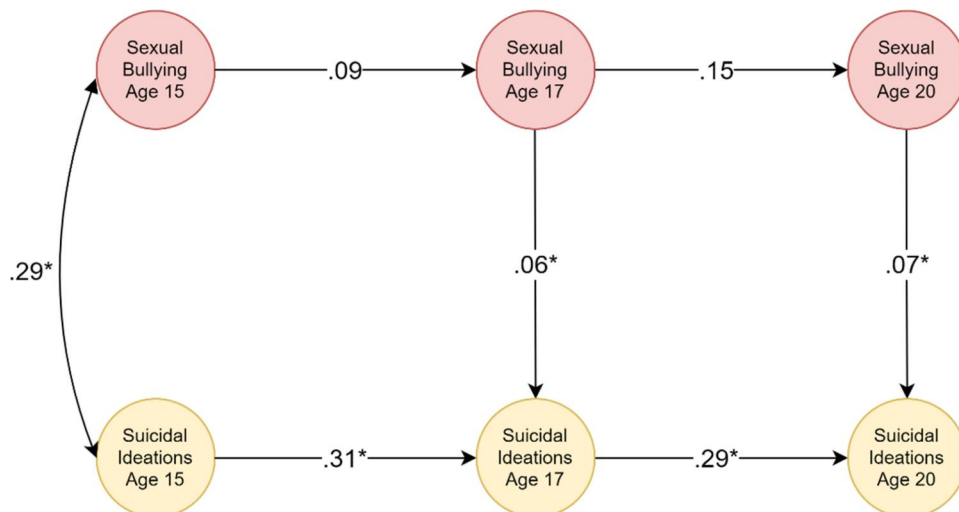


Figure 6. Standardized regression coefficients for the best fitting model for sexual bullying victimization and suicidal ideations. Random intercepts are omitted for clarity.

Table 4. Parameter estimates for RI-CLPM with invariant cross-lagged and invariant unidirectional reciprocal effects from victimization to internalizing problems.

ss	Estimate	Std. estimate	Standard error	p-value
Within-person autoregressive effects				
Age 17 suicidal ideations on age 15 suicidal ideations	.335	.310	.063	<.001*
Age 20 suicidal ideations on age 17 suicidal ideations	.258	.293	.060	<.001*
Age 17 sexual bullying on age 15 sexual bullying	.082	.088	.093	.348
Age 20 sexual bullying on age 17 sexual bullying	.152	.146	.091	.109
Within-person reciprocal effects				
Age 17 suicidal ideations on age 17 sexual bullying	.060	.056	.027	.035*
Age 20 suicidal ideations on age 20 sexual bullying	.060	.067	.031	.035*
Within-person covariances				
Age 11 suicidal ideations with age 11 sexual bullying	.068	.139	.055	.012*
Between-person covariances				
Random intercept suicidal ideations with random intercept sexual bullying	.050	.285	.098	.004*

Note. *significant at $p < 0.05$.

time points when the true data generating model does not contain such a path, but rather a *within* time point effect (B. Muthén & Asparouhov, 2022, 2024). To address this issue, we propose the use of the reciprocal RI-CLPM. Recently introduced by B. Muthén and Asparouhov (2022, 2024), this model allows for the modeling of directional concurrent effects. Specifically, in contrast to modeling concurrent associations only as residual covariances, reciprocal RI-CLPMs can include bidirectional regression paths within the same time point (B. Muthén & Asparouhov, 2022, 2024). This likely not only improves the accuracy of estimated cross-lagged effects in cases where a temporal sequence in variables measured at the same time point may be plausible. Additionally, it can give insights into directional effects occurring within shorter timeframes.

To illustrate how conclusions drawn from reciprocal RI-CLPMs may differ from analyses drawn from classic RI-CLPMs in an applied research context, we tested a series of RI-CLPMs using two empirical examples from the longitudinal z-proso study. Specifically, we analyzed the longitudinal associations between variables that were assessed using different reference time frames; thus making concurrent directional effects likely. We focused on the associations between bullying victimization (in the past year) and internalizing problems (in the past month) as well as between sexual bullying victimization (in the past year) and suicidal ideations (in the past month). Results suggested that conclusions drawn from reciprocal RI-CLPMs may differ from those drawn from classic RI-CLPMs.

Based on model fit, model parsimony, and theoretical plausibility of included paths, we found that a reciprocal RI-CLPM including a unidirectional concurrent path from bullying victimization to internalizing problems was the preferred model for explaining the associations between bullying victimization and

internalizing problems across ages 11 to 17. The results from this model further aligned with the inferences drawn based on the results from all conducted analyses. These collectively indicated that the directional links from internalizing problems to experiencing bullying victimization may take longer to manifest and can be accurately represented by cross-lagged paths. In contrast, the directional links from victimization to internalizing problems are likely to be observed due to short-term processes. This also captures the likely sequence of events implied by the different reference timeframes over which the two variables were measured.

It is important to clarify that these analyses were conducted primarily for demonstration purposes, focusing on the methodological implications of neglecting concurrent associations in classic RI-CLPMs, rather than addressing practical or theoretical research questions within the bullying victimization literature. Nonetheless, the results do align with some established findings. For instance, findings are supported by a meta-analysis of Quasi-Experimental studies on the consequences of bullying victimization (Schoeler et al., 2018). Specifically, this meta-analysis indicated that the harmful effects of bullying victimization were stronger in the short-term than in the long-term, particularly for internalizing problems. In contrast, findings on the longer-term effect of internalizing problems on increases in bullying victimization indicate that symptoms of internalizing problems in adolescents may precede bullying victimization over extended time frames. At first, internalizing symptoms such as social withdrawal may lead to challenges in connecting with peers. Down the line, these social deficits may escalate into peer problems and bullying victimization (Sentse et al., 2017).

When examining the associations between sexual bullying victimization and suicidal ideations, two interesting findings emerged when looking at the

results across all conducted analyses. We found a relatively consistent cross-lagged effect of experiencing sexual bullying victimization leading to a reduction in suicidal ideations over the age of 17 to 20 lag. However, examining concurrent pathways, we also found evidence for sexual bullying victimization leading to an increase in suicidal ideations at age 17. Examining possible mediation pathways *via* which sexual bullying victimization may affect suicidal ideation 3 years later, we found that the total effect of sexual bullying victimization at age 17 on suicidal ideations at age 20 was not in fact statistically significant. This suggests that examining the cross-lagged effect of sexual bullying victimization at age 17 on suicidal ideations at age 20 without also considering concurrent effects may lead to a biased conclusion. In fact, the model favored based on model fit, model parsimony, and theoretical plausibility suggested only concurrent effects of sexual bullying victimization leading to an increase in suicidal ideations.

Taken together, findings from this analysis suggested that it may be that the previously observed effect of experiencing sexual bullying victimization leading to decreases in suicidal ideations as estimated using a classic RI-CLPM in the current data (Zhu et al., 2022b, 2022a) does not represent the true effect but only one part of a complex process. Specifically, the observed within time point increase in suicidal ideations following sexual bullying victimization may indicate the immediate consequences of a traumatic shock. The subsequent decrease in suicidal ideation, on the other hand, may be reflective of a longer-term *regression to the mean* indicative of a (re-)adaption process following such a traumatic experience. Such a process has been observed in prior research, for instance in the context of post-trauma recovery. Specifically, Steenkamp et al. (2012) found evidence for most individuals showing very high levels of distress 1-month post sexual assault but more than 75% of individuals subsequently showing a gradual decline in symptoms over the following months. Similarly, Fletcher et al. (2021) found that time since trauma was a strong predictor of less severe symptoms of PTSD and further improvement over time. Considering the time span of 3 years over which the effect of sexual bullying victimization on suicidal ideations was measured in the current study, it is possible that similar processes may also be at play here. While a detailed comparison with the substantive victimization literature is beyond the scope of this paper, which focuses primarily on methodological aspects, it should be a focus of future research. Understanding these

post-trauma recovery processes may provide important insights into the long-term effects of bullying victimization.

Overall, results of the here conducted empirical analyses underscore the value of considering concurrent effects in random-intercept cross-lagged panel modeling. Considering also the evidence from simulation studies conducted by B. Muthén and Asparouhov (2022, 2024) that suggest that the reciprocal model reliably recovers true concurrent effects while their omission may lead to biased cross-lagged effects, we believe that the reciprocal RI-CLPM can provide valuable insights. It can shed light on directional effects between variables measured at the same measurement occasion. Further, it may improve the accuracy of estimated cross-lagged effects in cases where a temporal sequence in variables measured at the same time point may be likely.

When conducting analyses within a random-intercept cross-lagged panel modeling framework, we advise that researchers carefully consider which pathways (*within* or *across* time) are most likely to accurately reflect the data generating model underlying the observed data. Here, we also want to reiterate that reciprocal RI-CLPMs cannot be statistically distinguished from classic RI-CLPMs, thus, statistically, evidence for concurrent pathways cannot be used as evidence against cross-lagged effects or vice versa. This makes it particularly important to consider which pathways are theoretically plausible given the properties of the used measures, the study's design and theories relating to the construct under investigation before making inferences from any model. In contexts where it is not entirely clear which model most likely accurately reflects the underlying data, for example because reference time frames overlap or because reverse causality within a time point cannot be ruled out, we recommend that researchers consider multiple models with different specifications. At the same time, researchers should also consider the exceeding complexity for interpretation of concurrent bidirectional effects, and draw inferences based on the robustness of effects across all models. This can provide a more comprehensive understanding of the underlying data generating process and can thus help to mitigate potential biases and improve the validity of RI-CLPM analyses.

With regards to the empirical example on internalizing problems and bullying victimization, we note the following limitations. First, we were not able to include a latent measurement model due to convergence difficulties, likely owed to the complexity of the

conducted analyses. While psychometric properties of the used measures were generally favorable, the use of composite scores precluded controlling for measurement error, potentially weakening associations between the constructs under investigation. Moreover, the bullying victimization scale has been found to only be partially invariant in that the physical aggression item becomes less relevant at later ages (Murray et al., 2021). For the analysis of sexual bullying victimization and suicidal ideations, we relied on single item measures, validated in prior research (e.g., Steinhoff et al., 2021). However, using multi-item scales could provide a more comprehensive understanding of the constructs and reducing measurement error. Future research is thus needed to validate the empirical findings of the presented analyses. An additional limitation that needs to be considered is that longitudinal study designs, such as the design of the empirical study presented here, commonly rely on unbalanced assessment timings (e.g., one participant completed the study at age 11 and 1 month, whereas another completed the study at age 10 and 11 months). Future research is needed to test how these different issues imbalance affects the robustness of reciprocal and cross-lagged effects.

While reciprocal RI-CLPMs have strong potential for improving inferences drawn from longitudinal data, these models currently come with some important limitations. First, we here tested how reciprocal RI-CLPMs perform in relatively straightforward scenarios; that is for bivariate analyses across only relatively few measurement occasions. Further research is necessary to test how reciprocal RI-CLPMs perform in more complex scenarios. This includes analyses of longitudinal within-person mediation effects (Speyer et al., 2022) or analyses of moderation effects at the within as well as between-person level (Mulder & Hamaker, 2021; Speyer et al., 2023). Second, we note that reciprocal effects cannot be estimated for the first time point even though, based on theory, directional paths may be equally plausible. This limitation needs to be addressed in future research. Additionally, reciprocal RI-CLPMs with bidirectional regression paths require a set of constraints for model identification. They require the reduction of the overall number of parameters which can most easily be achieved by placing invariance constraints on the cross-lagged and/or reciprocal paths. This implies stationarity, that is, effects at time 1 are presumed to be identical to effects at time 2. This assumption may be problematic, for instance in the context of developmental research where effects are likely to change across

developmental stages. Further, additional constraints have to be placed on the reciprocals to avoid dual solutions. While these constraints themselves do not raise any specific issues, model results need to be carefully checked for positive R-squared values and non-zero reciprocal estimates to ensure that the model resulted in an admissible solution. Finally, research into causal inferences drawn from cross-lagged analyses has suggested that contemporaneous associations may be particularly relevant in the context of long time periods between measurement occasions (Leszczensky & Wolbring, 2022; Vaisey & Miles, 2017). Further research is warranted to explore how reciprocal RI-CLPMs perform in scenarios where concurrent/cross-lagged associations may be more or less likely depending on how much time that has passed between measurement occasions.

Conclusion

In summary, the empirical examples presented in the current paper emphasize the importance of carefully considering what concurrent effects may be at play when deciding on which model to use for the analysis of directional associations between variables over time. As it tends to be unclear which model is most likely to accurately reflect the underlying data generating model, for instance because reference timeframes overlap, we suggest considering multiple different models and to draw inferences based on the robustness of effects across all models.

Article information

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