Cross-Lagged Network Models

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Abstract

Network theory and accompanying methodology are becoming increasingly popular as an alternative to latent variable models for representing and, ultimately, understanding psychological constructs. The core feature of network models is that individual observed variables (e.g., symptoms of depression) can directly influence each other, resulting in an interconnected system. The dynamics of such a system give rise to emergent states of constructs (e.g., a depressive episode). Network modeling has been applied to cross-sectional data and intensive longitudinal designs (e.g., data collected using an Experience Sampling Method). Currently lacking in the methodological toolbox of network modeling is a method with the capacity to estimate network structures at the item level on longitudinal data with relatively few measurement occasions. As such, in this paper, we present a cross-lagged panel network model to reveal item-level longitudinal effects that occur within and across constructs over time. The proposed model uses a combination of regularized regression estimation and SEM to estimate auto-regressive and cross-lagged pathways that characterize the effects of observed components of psychological constructs on each other over time. We demonstrate the application of this model to longitudinal data on students' Commitment to School and Self-Esteem.

Keywords: Network Models, Cross-Lagged Panel Design, Cross-Lagged Networks.

Cross-lagged panel models (CLPMs) are common in developmental research because they allow researchers to make headway toward distinguishing the direction of causality between two or more related constructs (e.g., neuroticism, depression). Increasingly, researchers fit CLPMs in a structural equation modeling (SEM) framework, with constructs of interest modeled as latent variables underlying a set of observed measures (Finkel, 2008; Little, Preacher, Selig, & Card, 2007). In a latent variable CLPM, causal power is represented at the level of the latent construct: Constructs are presumed to affect each other over time (e.g., the latent construct 'neuroticism' affects the latent construct 'depression'). Recently, network models have been presented as an alternative to latent variable models for many psychological constructs. The key feature of network models is that relations are modeled at the level of the behaviors, thoughts, and feelings, that are queried in individual items rather than at the level of latent variables (Borsboom, 2008; Borsboom & Cramer, 2013; Cramer, Waldorp, van der Maas, & Borsboom, 2010; Cramer et al., 2012). For example, instead of a person's level on a latent "extraversion" construct causing that person both to dislike people and also to dislike parties, the network modeling approach allows liking people and liking parties to be directly related (e.g., disliking people makes a person dislike parties). Thinking about constructs in a network manner is particularly relevant—from a *conceptual* standpoint—in the case where either logic/common sense, and/or empirical evidence indicates that covariance between items is better explained by a direct relation (e.g., two symptoms of major depression: insomnia → fatigue) than by a latent variable (insomnia ← LV→ fatigue).

In the present paper, we introduce the *cross-lagged network model*, which extends the network modeling approach to a model for longitudinal panel data (i.e., data collected on a large sample of individuals at a *few* discrete measurement occasions). In a nutshell, this model will allow individual components of a construct to affect other components of the same, and other constructs, over time. As the network modeling approach has been adopted in many applied fields (e.g., clinical and personality psychology; Borsboom et al., 2021; Constantini, Saraulli & Perugini, 2020; McNally, 2020) where panel data are widely available, the cross-lagged network model presents a necessary addition to the network modeling toolbox.

In the remainder of this paper, we will first introduce cross-lagged panel models and network models. We then present the crossed-lagged panel network as a combination of these two methods. Throughout this article, we use a dataset of longitudinal panel data on two constructs, *commitment to school* and *self-esteem*, as an empirical example and will apply the proposed crossed-lagged panel network to these data. Finally, we discuss the strengths and limitations of the model more generally and offer suggestions for its use.

Cross-lagged Panel Models

In a cross-lagged panel design, two or more constructs are measured at two or more discrete measurement occasions. By regressing the set of variables at each occasion on the set of variables at the previous occasion, one can estimate the "cross-lagged" effect of each variable on the other over a particular time lag (i.e., whatever time lag separates the two measurement occasions), while controlling for the auto-regressive effect of each variable on itself. Because of the challenge with making causal inference from cross-lagged parameters (Hamaker, Kuiper, & Grasman, 2015), we interpret cross-lagged paths in terms of prediction and *not* in causal terms (a subject we will return to in the Discussion). That is, a regression path from variable X at occasion t to a variable Y at future occasion $t+1$ suggests that a change in X predicts a change in Y over the course of that specific time lag. Such predictive relations over time may generate causal *hypotheses* (Godfrey-Smith, 2009; Epskamp et al., 2018; Williamson, 2006): If X really causes Y, then regressing Y at occasion $t+1$ on X at occasion t, controlling for Y at occasion t, should produce a non-zero regression coefficient. Finding a non-zero regression coefficient is thus an important but not sufficient condition for determining causality (Barnett, Barreth, & Seth, 2009).

In a traditional CLPM, the variables at each measurement occasion are scale scores (i.e., sum scores of a set of items on some psychometric scale). In recent years, it is increasingly common for developmental researchers to use latent variables to represent the constructs of interest in a panel model (e.g., Johnson, Galambos, Finn, Neyer, & Horne, 2017). Figure 1 shows a CLPM with two latent variables and two measurement occasions. The cross-lagged paths (cl_{BA} and cl_{AB}) represent the predictive strength of each construct on the other at a later measurement occasion, controlling for the *auto-regressive* effects of each variable on itself (ar_A and ar_B).

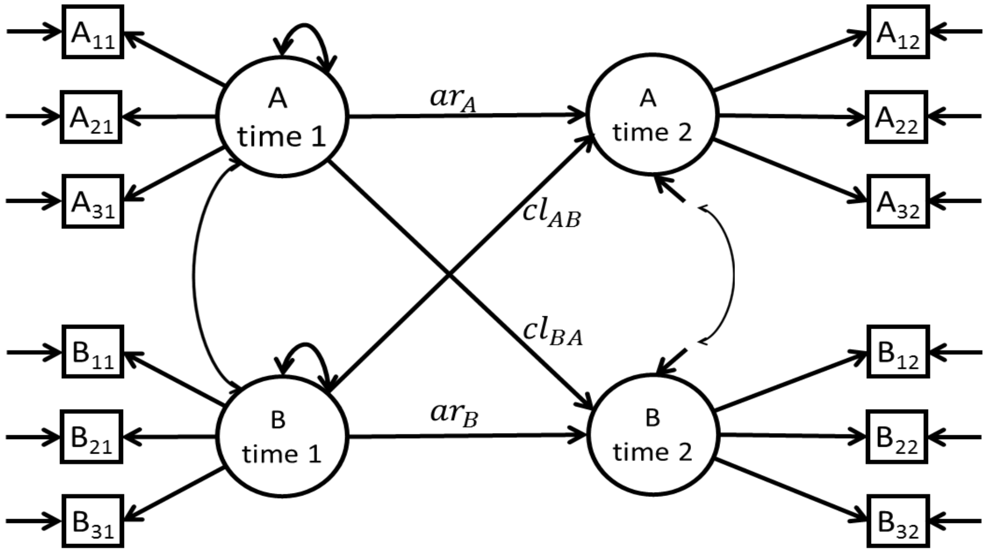

Figure 1. Cross-lagged panel model based on latent variables, with two constructs and two measurement occasions.

CLPMs are most appropriate when one has data on several constructs at a few discrete measurement occasions from a large group of individuals, and when the research questions center on predictive or potentially causal effects of these constructs over time. The CLPM has known limitations that we return to later, but despite these, it continues to be a popular and useful model to investigate relations among constructs with data gathered at a limited number of measurement occasions.

Network Models

The network approach to psychological constructs (Borsboom, 2008; Cramer, Waldorp, van der Maas & Borsboom, 2010) is based on the idea that high-level attributes (disorders, traits, abilities) may arise via lower-level processes by which individual attitudes, behaviors, symptoms, beliefs, and abilities interact with each other and, as such, form dynamic systems that result in certain outcomes (e.g., an episode of major depression, a high state of neuroticism, or a particular level of intelligence). Network models are an attempt to capture these lower-level processes by modeling direct relations among lower-level variables, rather than representing them as reflections of a single underlying high-level attribute (e.g., as in a latent variable model). Recent applications of network models to psychological data include personality (Beck & Jackson, 2020; Cramer et al., 2012; Taylor, Fong, & Asmundson, 2021), depression (Albers, McNally, Heeren, De Wit, & Fried, 2019; Cramer, van Borkulo, Giltay, van der Maas, Kendler, Scheffer, & Borsboom, 2016; Zavlis et al., 2022), schizophrenia (Isvoranu, van Borkulo, Boyette, Wigman, Vinkers, & Borsboom, 2016), quality of life (Kossakowski, Epskamp, Kieffer, van Borkulo, Rhemtulla, & Borsboom, 2016), subjective well-being (Deserno, Borsboom, Begeer, & Geurts, 2016), autism and obsessive-compulsive disorder (Ruzzano, Borsboom, & Geurts, 2014), post-traumatic stress disorder (Armour, Greene, Contractor, Dixon-Gordon, & Ross, 2020; McNally, Robinaugh, Wu, Gwyneth, Wang, Deserno, & Borsboom, 2014), complicated grief (Robinaugh, Millner, & McNally, 2016), and substance abuse (Rhemtulla, Fried, Aggen, Tuerlinckx, Kendler, Borsboom, 2016).

In a typical network model, a set of items measuring a construct (e.g., the items on an extraversion scale) are represented by a set of network *nodes*. The relations between these nodes are represented by *edges*. Networks estimated from cross-sectional data (i.e., data gathered at a single measurement occasion from a large group of individuals) are typically *undirected* conditional association networks; that is, each edge represents a partial correlation between the nodes (variables) that it connects, controlling for all other nodes in the network. Conditional association networks can be estimated using $l1$-regularized regression techniques, which push many edges to exactly zero, resulting in the "sparsest" network that can still account for associations in the data. Alternatively, conditional association networks can be estimated using non-regularized techniques where sparsity is induced using edge significance levels or BIC model selection[1].

Figure 2 shows a non-regularized partial correlation network for the constructs *commitment to school* (7 items) and *self-esteem* (10 items), based on data from the Iowa Youth and Families Project (Conger et al., 2011) at the first wave of data collection (i.e., students in 7th grade; data details are presented in the "Data" section below). Green lines represent conditional positive relations among variables; thicker and darker lines represent stronger relations. The layout of nodes is chosen by an algorithm that places more strongly connected nodes closer together (Fruchterman & Reingold, 1991). Thus, one can see from the thick green lines and the placement of the variables that the items within each construct cluster together, suggesting that

[1] Software for estimating partial correlation networks includes the EBICglasso or ggmModSelect functions for Gaussian data in the R qgraph package (Epskamp, Cramer, Waldorp, Schmittmann, & Borsboom, 2012) and the R IsingFit package for binary data (van Borkulo, Borsboom, Epskamp, Blanken, Bosschloo, Schoevers, & Waldorp, 2014).

these constructs are conceptually coherent. Within each construct, certain pairs of items are much more strongly connected than others; for example, the items "I like school a lot" (reverse coded) and "School bores me" are more strongly related than either of those items are to the item "I try hard at school" (reverse coded). This network also reveals some connections across the two constructs, including a link between the *commitment to school* item, "I don't do well at school" and the *self-esteem* item, "I'm a failure". These cross-network connections generate hypotheses about the pathways by which the two constructs could influence each other over time.

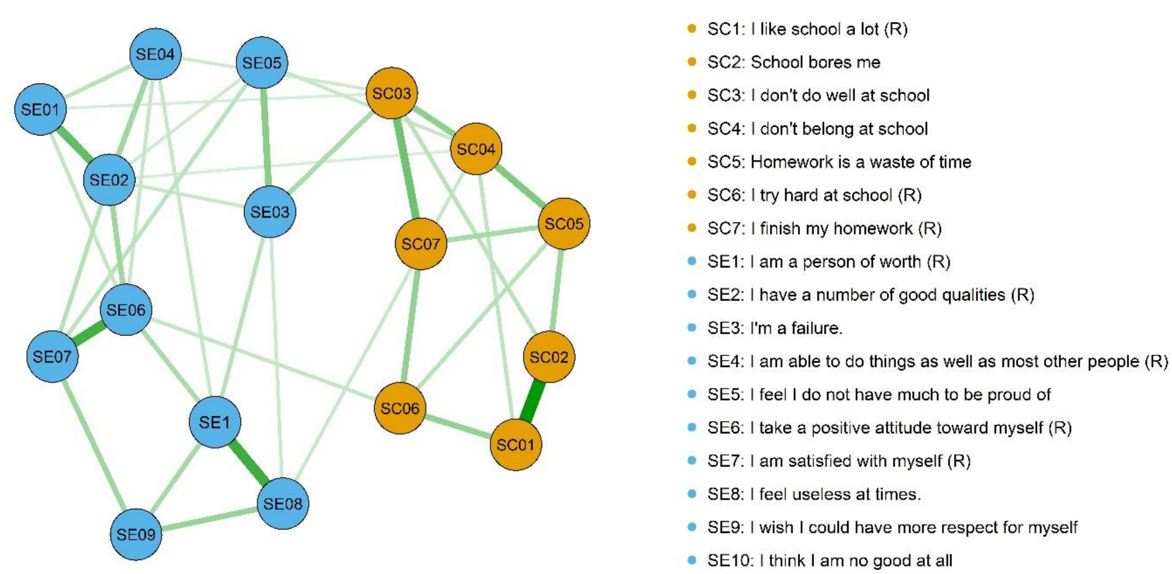

Figure 2. Non-regularized cross-sectional partial correlation network of Commitment to School (orange) and Self-Esteem (blue)

Many network models have also been developed for intensive longitudinal time-series data, that is, data in which a single individual or a group of individuals provide many (e.g., 100 or more) data points that are typically closely spaced in time (e.g., hours apart). Time-series network models include vector auto-regressive (VAR) models that model variables at occasion $t + 1$ as a function of those at occasion t within a single individual (e.g., Epskamp, Waldorp, Mõttus, & Borsboom, 2017; Gates & Molenaar, 2012). In particular, Epskamp et al. (2017) have proposed a graphical-VAR approach that estimates directed paths across time, as well as contemporaneous networks for individuals and between subjects. The VAR approach is an incredibly powerful model for discovering predictive relations—and hence, potential causal processes—at the level of individuals. The VAR approach can also be used on panel data, but it requires the assumption of stationarity across the course of the time points (i.e., equal means and covariances across all timepoints) and returns a single network to represent all timepoints. Although this assumption is often tenable with intensive longitudinal data gathered over the course of hours or days, it is unlikely to hold when the processes being measured represent development over the course of months or years or longer, as many panel data designs do.

In the following section, we present a model that can be used to estimate cross-lagged predictive relations among the individual components of multiple constructs over time. As an empirical example, we use longitudinal panel data on two constructs, *commitment to school* and *self-esteem*. In addition to highlighting predictive relations, the proposed model will yield information about which variables in the network are most central to the construct, and about pairs or groups of variables that are tightly clustered and may thus play a unique role with respect to the construct.

Cross-lagged Panel Networks

In the previous sections, we described CLPMs, which highlight pathways among constructs over a few fixed measurement occasions, and network models, which reveal unique pathways among the constituent variables of a construct. We combine these two approaches to form cross-lagged panel *networks* (CLPNs). The key feature of a CLPN is that the relations among individual items are modeled as directed paths across time, reflecting the variance shared between a variable at occasion t and another (or the same) variable at occasion $t + 1$, controlling for all other variables at occasion t. The interpretation of these directed paths is subject to the same constraints as those of the traditional CLPM described above; that is, paths may be interpreted as predictive relations and/or as causal-hypothesis-generating. Similarly, the CLPN cannot estimate differences in predictive patterns across individuals (i.e., every person is assumed to have the same pattern of predictive relations over time) but it can allow different predictive patterns across different measurement occasions (e.g., predictive patterns from 8th grade to 9th grade may differ from those from 9th to 10th grade).

There are strong theoretical and pragmatic benefits to the proposed model. In theoretical terms, the CLPN model can suggest mechanisms by which constructs sustain themselves (e.g., beliefs and behaviors that make up self-esteem may influence each other over time, creating a positive feedback loop and resulting in the persistence of self-esteem as a stable trait) and may lead to changes in other constructs over time (e.g., beliefs and behaviors related to self-esteem may influence a person's ability to make and maintain friendships over time, resulting in a positive association between the broad constructs of self-esteem and friendship quality). Because a CLPM with latent variables makes the strong assumption that all predictive effects in the observed data are explained by relations among the latent constructs, the latent variable CLPM has no potential to discover which individual components of such constructs have the strongest influence on longitudinal change and stability. In contrast, the CLPN can uncover the individual behaviors, beliefs, attitudes, traits, or symptoms that are responsible for these auto-regressive and cross-lagged longitudinal construct relations. For example, consider two items of the *commitment to school* scale: *success in school* and *enjoyment of school.* The CLPN allows that not doing well in school may affect a student's later enjoyment of school over and above that student's mean-level change in school commitment. Moreover, the CLPN allows individual items belonging to one construct to affect change in individual items belonging to a different construct at a later time. For example, not doing well in school may affect a student's later feelings of being a failure over and above the broader effect of school commitment on self-esteem. If individual components of one construct have unique effects on other constructs, the CLPN will highlight these effects. Learning *which* items are primarily responsible for the relations among constructs over time may generate more fine-grained descriptions and theories of how constructs relate to each other.

A key benefit of this approach is that we do not need the assumption of stationarity to estimate the model, and, as such, can identify when the patterns of effects vary across timepoints. The cost of this flexibility is that the CLPN has many more potential paths to estimate and interpret, compared to a traditional CLPM. For example, whereas a CLPM with two latent constructs, each measured by 10 items at 3 measurement occasions, would produce 4 auto-regressive coefficients and 4 cross-lagged paths; a CLPN based on the same data would produce 40 auto-regressive paths (i.e., those connecting each variable at each measurement occasion to the same variable at the next occasion) and 740 cross-lagged paths (connecting each variable at each occasion to each other variable at the subsequent occasion). While it may be possible to estimate 800 regression coefficients, it is not feasible to interpret them individually.

The CLPN deals with this problem by using a hybrid estimation approach. The initial model is selected using lasso regression (a regularized approach) which fixes the smallest coefficients to exactly zero, thus reducing the number of freely-estimated paths. Although regularization decreases the parameter set which increases the ease of model estimation and interpretation, it also produces biased estimates (Fan, Liao, & Liu, 2016). In addition, lasso regression is known to have both high sensitivity and a high false positive rate (Kuismin, & Sillanpää, 2016). As such, we propose a follow-up step to further prune the model and obtain non-regularized coefficients. We suggest estimating the model selected by the regularized approach as a structural equation model (SEM) and using parameter significance to further prune the model. After finalizing the model, summary measures can be computed such as in-prediction and out-prediction, which reflect the extent to which particular variables (nodes) can be predicted and the extent to which they predict other variables over time, respectively.

Next, we briefly describe the technical details of our proposed model. We then apply the model to the constructs *commitment to school* and *self-esteem* and *describe* each step of the analysis and offer suggestions for how the results may be interpreted.

Methodological Details

The process of producing a CLPN model can be broken down into four steps. The first step involves collapsing overlapping items to reduce the set of variables submitted to the CLPN analysis. The second step involves fitting a series of regularized regression models to select the initial CLPN model. The third step is to re-estimate the model selected in step 2 as an SEM obtaining non-regularized estimates for the cross-lagged and auto-regressive coefficients across time. Finally, the fourth step is to summarize the results by producing plots and computing summary statistics such as nodewise in-prediction and nodewise out-prediction. We describe these steps in the following sections.

Collapsing Nodes

The guiding intuition behind network modeling of psychological constructs is that causal power may reside at a much lower level of specificity than the broad constructs that are typically granted causal power (Cramer et al., 2012). But there is no guarantee that the particular items used to assess a construct are at the appropriate level of generality to capture these causal effects. In particular for many cognitive and affective constructs, it is not unusual to have sets of items that are highly overlapping. While a typical assessment of psychopathology may contain a single item to represent each symptom, a self-esteem questionnaire might include all of the items, “I feel good about myself”, “I am satisfied with myself”, and “I like myself the way I am”. Given a high degree of conceptual overlap, a reasonable expectation is that these three items behave in the same way (i.e., have the same effects and predictors) in the overall network architecture. Thus, we recommend collapsing highly similar items (by summing or averaging scores on these items) to achieve a set of variables that are plausibly autonomous causal agents, thus simplifying the model, reducing the possibility of spurious relations, and rendering the results more interpretable[2].

It is important to stress that the goal of this analysis step is not to reduce a large set of items to a small set of underlying dimensions, but simply to remove the redundancy that arises from nearly-identical items that query the same manifest behavior. Dimension-reduction techniques such as principal components analysis, singular value decomposition, and factor analysis aim to reduce a large set of items to just a few broad dimensions. This aim is antithetical to the goals of the network approach, which are to understand the connections among low-level behaviors, beliefs, attitudes, abilities, symptoms, or traits. Thus, while it would be possible to use statistical dimension-reduction techniques to decide which items to collapse, we strongly

[2] Data-driven approaches can also be used to detect highly similar nodes (e.g., the UVA function from the EGAnet R package; Christensen, Garrido, & Golino, 2023)

recommend against it. As a central goal of network analysis is to move away from abstractions and toward explaining constructs in terms of concrete observable variables, applying statistical grouping methods is likely to be counterproductive.

We further recommend that researchers err on the side of not collapsing too much, for the same reason: the more variables are collapsed, the more removed the composite gets from a concrete observable behavior/belief/attitude. As the goal is to foster an understanding of the relations among low-level variables, it is important that only variables that are highly similar, that is, variables that are essentially rephrased versions of each other, be collapsed.

Regularized Regressions

Once the data have been condensed into a set of appropriate variables, the next step is to estimate linear regression coefficients of each variable on itself and each other variable, from one measurement occasion to the next. We start with the first two measurement occasions (although the CLPN can easily be extended to include more than two timepoints), denoted T1 (for time 1) and T2 (for time 2) henceforth, according to the model $\boldsymbol{x}_{\mathrm{T2}} = \boldsymbol{\beta_0} + \boldsymbol{B}\boldsymbol{x}_{\mathrm{T1}} + \boldsymbol{\varepsilon}$, where $\boldsymbol{x_{T1}}$ and $\boldsymbol{x_{T2}}$ are vectors containing all p variables at T1 and T2, respectively, $\boldsymbol{\beta_0}$ is a vector of intercepts for the p variables at T2, $\boldsymbol{B}$ is a $p \times p$ matrix of linear regression coefficients[3] of all p variables at T2 on those at T1, and $\boldsymbol{\varepsilon}$ is a vector of residuals for each variable. The model can be extended to more measurement occasions by regressing the variables at each subsequent measurement occasion on the previous occasion.

If the sample size is large enough (at a minimum, sample size must be greater than the total number of variables at all measurement occasions for the covariance matrix to be positive

[3] We assume that the data are continuous and normally distributed. However, the model can readily be extended to allow for alternative distributions by using generalized linear model with a link function, e.g., a logit link for binary variables.

definite), the model can be estimated in a single step in an SEM framework. However, in the following we estimate a series of univariate linear regression models of the form $x_{j,\mathrm{T2}} = \beta_{0,j} + \boldsymbol{\beta}'_j \boldsymbol{x}_{\mathrm{T1}} + \varepsilon_j$, where $x_{j,\mathrm{T2}}$ is the *j*th variable at T2, β_0 is its intercept, $\boldsymbol{\beta}_j$ is the corresponding vector of regression coefficients that predict it from the vector $\boldsymbol{x}_{\mathrm{T1}}$ containing all *p* variables at T1, and ε_j is its residual. The benefit of the univariate approach is that it allows us to use available regularized regression software to estimate the model, resulting in a more parsimonious model that can be estimated even with small samples and many variables.

At this step, regression coefficients are estimated using lasso regression, a penalized regression approach that applies an ℓ_1 penalty on the estimated regression coefficients (Friedman, Hastie, & Tibshirani, 2010). This estimation technique has the effect of shrinking small regression paths to exactly zero, thus achieving a sparse solution. The ℓ_1 penalty is just one possible penalty that can be used to address the problem of overfitting, which is important when estimating a regression with a large number of predictors (the ℓ_2 penalty, i.e., ridge regression, is another possibility). The rationale for using lasso regression is that, on the assumption that some paths are truly zero, it will set to zero those paths that are most likely *not* to exist, in addition to estimating coefficients for non-zero paths. The result is a sparse network, in which many of the paths from variables at T1 to variables at T2 will be estimated as exactly zero.

The regularized regression estimates are the ones that minimize

$\frac{1}{N}\sum_{i=1}^{N} l\left(x_{i,j,T2}, \hat{\beta}_{0,j} + \widehat{\boldsymbol{\beta}}'_j \boldsymbol{x}_{i,T1}\right) + \lambda_j \left\|\widehat{\boldsymbol{\beta}}_j\right\|_1$, where $i = 1...N$ denotes individuals. Thus, what is minimized is the sum of individual likelihoods plus a penalty, $\lambda_j \left\|\widehat{\boldsymbol{\beta}}_j\right\|_1$in which $\left\|\widehat{\boldsymbol{\beta}}_j\right\|_1$ denotes the sum of absolute values of the coefficients in $\widehat{\boldsymbol{\beta}}_j$, and λ_j is a tuning parameter that determines the strength of the penalty. When λ_j is zero, the penalty drops away and we are left with OLS regression. As λ_j increases, all the coefficients in $\widehat{\boldsymbol{\beta}}_j$ will eventually be shrunk to zero. Though there are many criteria that can be applied to choose λ_j, here we use 10-fold cross-validation: Regression estimates are obtained for a sequence of 100 λ values, and the one that produces the lowest cross-validation error is chosen.

Lasso regression can help overcome estimation challenges in high-dimensional or near high-dimensional settings by shrinking the parameter space (Fan et al., 2016). Lasso regression also minimizes overfitting and so its results are more generalizable (i.e., increases predictive accuracy) than ordinary least-squares (OLS) estimates (McNeish, 2015). However, lasso regression also biases the non-zero edges towards zero. Additionally, recent research has shown that the cross-validation approach to selecting λ_j has extremely high sensitivity (i.e.,of the true existing edges, a very high proportion is correctly included in the model). The trade-off is that the cross-validation approach often has a high false positive rate and this false positive rate does not diminish with increased sample size (Kuismin & Sillanpaa, 2016). In other words, paths that are estimated to be zero in CV are very likely to be true zeroes, but many paths that are not set to zero may be false positives. Using regularized regression can help initially estimate the model. But, given the high false positive rate and the biased estimates, we want a further step to prune the model and get non-regularized estimates for interpretation.

Model Pruning and Estimating Edge Weights

The regularized regressions from the previous step provide us with a pruned starting model in which a subset of the T1 variables will predict the T2 variables. Since the regularized model is sparser than the full model where all possible edges estimated, it may be more feasible to estimate it using a non-regularized regression approach. The paths that are estimated to be zero in the regularized regression results are fixed to zero in this step. This can be done by estimating a series of univariate linear regression models of the form $\boldsymbol{x}_{\boldsymbol{j},\mathrm{T2}} = \boldsymbol{\beta}_{\boldsymbol{0},\boldsymbol{j}} + \boldsymbol{\beta}_{\boldsymbol{j}}'\boldsymbol{x}_{\mathrm{S(T1)}} + \boldsymbol{\varepsilon}_{\boldsymbol{j}}$, where $\boldsymbol{x}_{\mathrm{S(T1)}}$ is a smaller or equal set of edges compared to $\boldsymbol{x}_{\mathrm{(T1)}}$. Alternatively, the series of univariate linear regression models can be fitted simultaneously within a SEM framework. The SEM approach enables some nice features, like allowing for residual covariances within time point and carrying out model comparisons between more and less constrained versions of the models.

Cross-time constraints

When more than two measurement occasions are available to model, it may be of interest to investigate whether the predictive relations across successive occasions are equal (e.g., if the paths from 7^{th} to 8^{th} grade are equivalent to those from 8^{th} to 9^{th} grade). This question can be answered by fitting two nested models within a SEM framework and comparing their fit. The first SEM model is an unconstrained model that simultaneously estimates auto-regressive and cross-lagged paths across all neighboring pairs of measurement occasions. This model is "unconstrained" because it allows paths to take on different values across subsequent intervals. It is important that zeroes be imposed consistently across each pair of measurement occasions in the SEM model to ensure that the next (constrained) model is nested within it. There is no guarantee that the previous estimation steps will produce a consistent pattern of zeroes across occasions (e.g., the path from variable 1 to variable 2 may be non-zero from T1 to T2, but zero from T2 to T3), so it is necessary to use some decision rule to choose which paths to set to zero consistently across all measurement intervals. A conservative rule would be to constrain a path to zero only if it is estimated to be zero across every neighboring pair of occasions. A more liberal rule would be to constrain a path to zero if it estimated to be zero across the majority of intervals. We recommend using the conservative rule unless there are good reasons to prefer a more sparse/parsimonious network. Finally, when estimating the full model with multiple measurement occasions, residuals within each measurement occasion should be allowed to covary, to capture shared variance between each pair of variables in the network that can be attributed to effects within a time point (e.g., direct causal effects and common-cause effects that occur between measurement intervals).

The second (constrained) model is identical to the first but with cross-time constraints imposed, such that the set of paths from T1 to T2 is constrained to be equal to the set of paths from T2 to T3, and so on. Once both unconstrained and constrained models have been fit to the data, they can be compared using a nested chi-square difference test, in addition to approximate fit measures (e.g., $RMSEA_D$; Savalei, Brace & Fouladi, 2023) and information criteria (e.g., AIC and BIC). Based on the results of these fit comparisons, the final selected model may be either unconstrained (different predictive relations over timepoints) or partly constrained (the same predictive relations over time points).

In-prediction and Out-prediction

The final selected model (either unconstrained across occasions, or constrained, depending on the results of the model comparison in the previous step) can be summarized into two measures of variable centrality: *In-prediction* is the extent to which each variable is predicted by other variables in the network, and *out-prediction* is the extent to which each variable predicts other variables in the network. In-prediction is simply the proportion of variance in each variable at a measurement occasion that is accounted for by the complete set of variables at the previous occasion, and as such it can range in value from 0 to 1:

$$inPred_j = \frac{var(\hat{x}_{j,\mathrm{T2}})}{var(x_{j,\mathrm{T2}})} = \frac{var\left(\hat{\boldsymbol{\beta}}'_j \boldsymbol{x}_{T1}\right)}{var(x_{j,\mathrm{T2}})}.$$

Researchers may be particularly interested in two more specific in-prediction measures: *cross-lagged in-prediction* is the proportion of variance accounted for by all *other* variables at the previous measurement occasion, that is, cross-lagged in-prediction excludes the auto-regressive path, *within-construct in-prediction* is the proportion of variance accounted for by all the variables within the same construct, excluding the auto-regressive effect, and *cross-construct in-prediction* is the proportion of variance accounted for by all variables that belong to a different construct at the previous measurement occasion.

Out-prediction captures the average proportion of variance across all variables at the next measurement occasion (e.g., T2) that is accounted for by a single target variable at the previous occasion (e.g., T1):

$$outPred_j = \left(\frac{1}{p}\right) \sum_{k=1}^{p} \frac{var\left(\hat{\beta}_{x_{k,\mathrm{T2}} x_{j,\mathrm{T1}}} x_{j,\mathrm{T1}}\right)}{var\left(x_{k,\mathrm{T2}}\right)}.$$

Like in-prediction, out-prediction values can range from 0-1, though they will typically be substantially lower than in-prediction (an out-prediction value of 1 would indicate that a variable accounts for *all* of the variance in *all* variables at the subsequent measurement occasion). As with in-prediction, we can define two narrower versions of out-prediction: *cross-lagged out-prediction* averages the predictive effects over all variables except the one that is doing the predicting, *within-construct out-prediction* averages the predictive effects across only those variables that belong to the same construct (excluding the auto-regressive predictive effect) and *cross-construct out-prediction* averages the predictive effects across only those variables that belong to a different construct. Each of these in- and out-prediction measures can be computed from the model estimates produced in the previous step; no new models are estimated.

If the model includes more than two constructs, in-prediction and out-prediction could be computed separately for the effect of each variable on/from variables belonging to each other construct. All measures of in-prediction and out-prediction can be computed for each pair of adjacent measurement occasions. If cross-time constraints have been imposed, then these measures will be identical across occasions.

Knowing the stability of an estimate (e.g., its fluctuation in response to sampling variability) is important for calibrating interpretations, and as such, we can use bootstrapping to obtain stability intervals around each of the in- and out-prediction estimates. A bootstrapping approach starts by drawing (with replacement) *m* samples of size *n* from the original dataset, where *n* is the size of the original data set. In and out-prediction indices are calculated from each of the *m* samples to create a bootstrapped sampling distribution of these indices. These sampling distributions are then used to compute confidence intervals around each estimate[4].

Example: Commitment to School and Self-Esteem

To demonstrate estimation and interpretation of a cross-lagged network model, we used publicly available data from the Iowa Youth and Families Project (Conger et al., 2011) on the Commitment to School and Self-Esteem scales. We chose these constructs because they each plausibly feature causal interactions among the attitudes that are measured by individual scale items. For example, the Commitment to School scale measures the extent to which children do well in school ("I don't do well at school") and their enjoyment of school ("I like school a lot"), which are likely to affect each other directly.

Data

The Iowa Youth and Families Project collected yearly data from an initial sample of 451 students who were in 7th grade in 1989 until 1992. Commitment to School was measured by

[4] Researchers could also use this approach to get bootstrapped edge weights in addition to stability estimates.

seven items developed by Robert Conger for the Iowa Youth and Families Project, and Self-Esteem was measured with the Rosenberg Self-Esteem Scale (Rosenberg, 1965). Participants answered each item on a 5-point scale on which the endpoints corresponded to “Strongly Agree” and “Strongly Disagree”; items were coded such that *lower* scores correspond to higher levels of commitment to school or self-esteem. Table 1 displays the final set of items that were included in the CLPN analysis.

Data on these constructs are available at 4 waves, each separated by one year (1989 – 1992). Of the 451 students who participated in the first wave, 424, 407, and 403 participated in waves 2-4, respectively; 395 students provided data at all 4 waves, 11 of these students were missing data on a single item at one wave. Because glmnet does not accommodate incomplete cases, in the first step of the analysis (regularized regression analyses with glmnet) we remove all cases with missing data. In subsequent steps (SEM analyses) the full dataset can be used and missing data is handled using full information maximum likelihood estimation.

Table 1. Commitment to School and Self-Esteem Items

Commitment to School	
SC1	In general, I like school a lot. (R)
SC2	School bores me.
SC3	I don’t do well at school .
SC4	I don’t feel like I really belong at school.
SC5	Homework is a waste of time.
SC6	I try hard at school. (R)
SC7	I usually finish my homework (R)
Self-Esteem	
SE1	I feel that I'm a person of worth, at least on an equal level with others. (R)
SE2	I feel that I have a number of good qualities. (R)
SE3	All in all, I am inclined to feel that I'm a failure.
SE4	I am able to do things as well as most other people. (R)
SE5	I feel I do not have much to be proud of.
SE6	I take a positive attitude toward myself. (R)
SE7	On the whole, I am satisfied with myself. (R)
SE8	I certainly feel useless at times.
SE9	I wish I could have more respect for myself.
SE10	At times I think I am no good at all.

Note. Items marked with (R) were reverse-coded.

Analysis and Results

All analyses were done in R (R Core Team, 2016). CLPN regressions were estimated with the glmnet package (Friedman, Hastie, & Tibshirani, 2010) and the lavaan package for SEM (Rosseel, 2012) , and networks were plotted using the qgraph package (Epskamp et al., 2012). R code to reproduce all analyses and CLPN figures is available at osf.io/9h5nj.

Latent Variable CLPM. For the sake of providing a baseline comparison, we begin by presenting the traditional CLPM based on latent variables. We defined two latent variables, Commitment to School and Self-Esteem, each indicated by the set of items presented in Table 1, at each of the four measurement occasions. To ensure that the latent variables are comparable over time, we imposed weak measurement invariance; that is, the unstandardized factor loadings were constrained to be the same at all four measurement occasions. We fit the model in lavaan, using full information maximum likelihood to deal with missing data, and robust corrections to the standard errors and test statistic to deal with violations of the normality assumption (estimator = MLR). The weak invariance constraint did not significantly reduce fit compared to the model that allowed loadings to differ over time, $\chi^2_{\Delta}(df = 45) = 47.75, p = .36$. We further constrained the auto-regressive and cross-lagged paths to be constant across each pair of measurement occasions; this model fit significantly worse than the unconstrained model, but an examination of approximate fit indices and information criteria suggested that its fit was not substantially worse, and by some criteria (CFI, BIC) fit was improved by imposing these constraints:$\chi^2_{\Delta}(df = 8) = 25.00, p = .002, \Delta CFI = -.001, \Delta AIC = 11.46, \Delta BIC = -21.43, RMSEA_D$.

As is typical in latent variable CLPM analyses, we allowed each item's residual to covary across measurement occasions, to account for stable item-specific variance that is unrelated to the latent factor (Little et al., 2007; Little, 2013; Mayer, 1986). The resulting model with cross-time constraints is depicted in Figure 3 (only two measurement occasions are shown because all path coefficients are identical across time). The model fit was reasonable by conventional criteria: χ^2 $(df = 2145) = 3984.08, p < .001, RMSEA = .047(.044, .049), CFI = .86, TLI = .85$. This analysis revealed small cross-lagged coefficients, only one of which was significantly different from zero at the $\alpha = .05$ level (SE → SC, $\hat{b} = .09$, $p = .046$; SC → SE, $\hat{b} = .04$, $p = .14$). On the basis of this analysis, one would conclude that the unique predictive effects of school commitment on Self-Esteem and vice-versa are weak to non-existent.

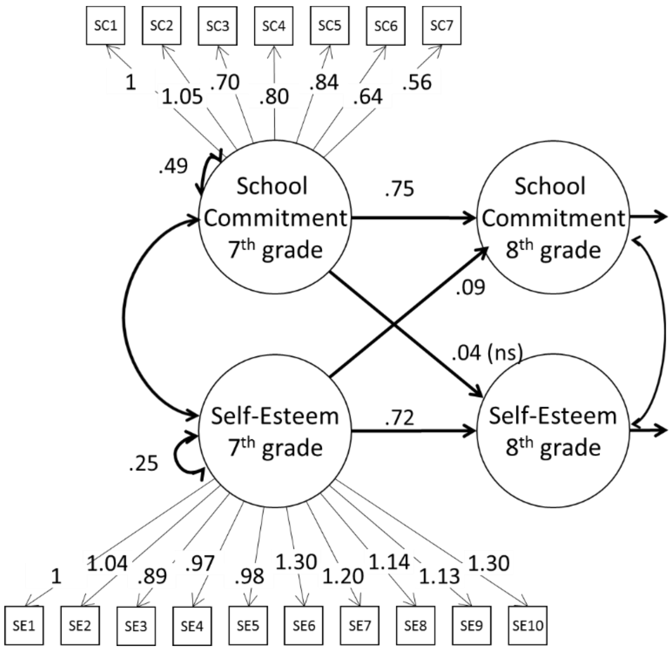

Figure 3. *Latent variable CLPM results. For clarity, only the first two measurement occasions are depicted and the measurement model is only shown for the first occasion. All 4 years were included in the model; auto-regressive and cross-lagged paths were constrained to be equal across each pair of occasions. Unstandardized factor loadings were also constrained to be equal at each measurement occasion. Residuals of each item were allowed to covary across occasions (not shown). Residual variances were free to vary across occasions.*

CLPN. Next, we followed the steps presented in the Methodological Details section to fit a cross-lagged panel network model. We opted not to collapse any overlapping variables, because we did not see items that were rephrasing of the same question. Thus, we first fit a series of regularized regressions to obtain our initial model. Next, we took that model and re-estimated it in a SEM framework allowing the residuals of variables within the same timepoint to covary[5]. We used the full-information estimation method with robust corrections to the fit statistics. This

[5] These covarying residuals capture shared variance between each pair of variables in the network that can be attributed to effects within a time point (e.g., direct causal effects and common-cause effects that occur between measurement intervals.

model fits well; $\chi^2\ (df = 1277) = 1653.76, p < .001; RMSEA = .025(.02, .029); CFI = .97, TLI = .95$ (robust statistics reported). The significant (p < .05) paths from the non-regularized analysis. are plotted in Figure 4 as three directed networks, in which arrows represent cross-time effects (e.g., an arrow from SE4 → SC4 represents a path from SE4 at one measurement occasion to SC4 at the subsequent occasion). The arrows that start and end at the same node represent auto-regressive paths (e.g., the path from SE4 at one measurement to SE4 at the subsequent measurement occasion. Arrow thickness/darkness represents the relative strength of these effects (thicker arrows represent stronger relations) and color represents the direction of the effect (green arrows represent positive effects). The placement of the variables is determined by the Fruchterman-Reingold algorithm described earlier, applied to the first measurement interval (i.e. 7^{th} to 8^{th} grade) and fixed to have the same layout for the subsequent two intervals for ease of comparison.

In accordance with the CLPM model, the auto-regressive paths (e.g., the effect of SC1 at 7^{th} grade on SC1 at 8^{th} grade) tended to be stronger than cross-lagged paths. The auto-regressive paths capture all stability in individual items over time, including construct-related stability as well as any stable unique variance (e.g., a response set that leads participants to answer questions in idiosyncratic ways may be stable across measurement occasions—such an effect would be expected to appear in the auto-regressive paths).

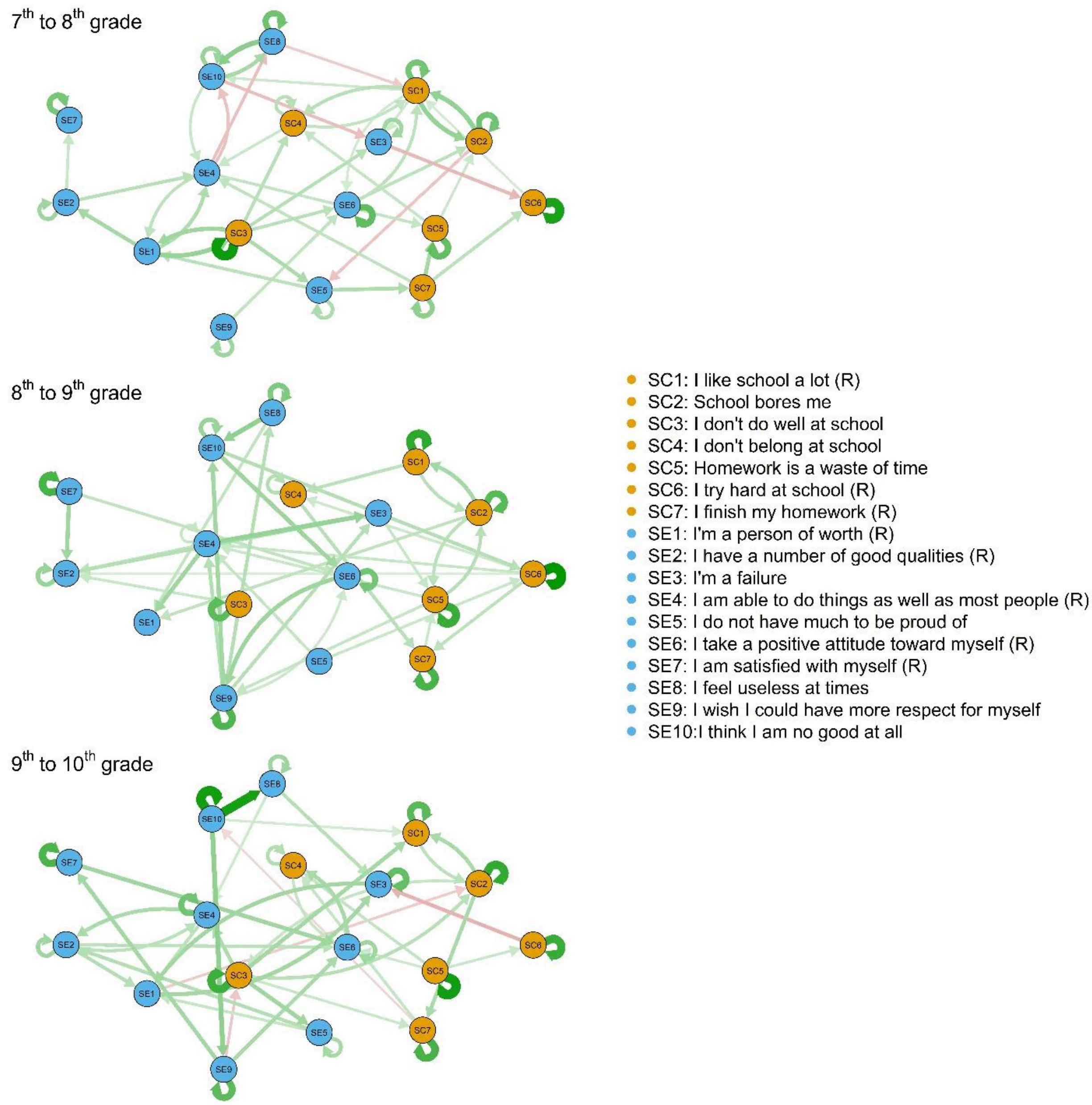

Figure 4. CLPN estimated using a hybrid approach. Relations across subsequent measurement occasions were allowed to differ.

The next modeling step is to test whether cross-time constraints can be imposed across the 3 measurement intervals. To do this, we first fit an unconstrained CLPN model, where only the paths that were estimated to be zero at all three measurement intervals were fixed to zero, and every other cross-lagged and autoregressive path was freely estimated. We again used the full-information estimation method with robust corrections to the fit statistics. This model fit well; $\chi^2\ (df = 987) = 1483.22, p < .001; RMSEA = .033(.029, .037); CFI = .96, TLI = .92$ (robust statistics reported). Second, we fit a model with cross-time constraints imposed, and found similarly good fit, $\chi^2\ (df = 1485) = 2197.63, p < .001; RMSEA = .033(.030, .036); CFI = .94, TLI = .92$. Because the model with cross-time constraints is nested within the unconstrained model, we can compare the models statistically. The chi-square difference test finds a significant difference, $\chi^2_{diff}(df = 498) = 714.4, p < .001$. This significant difference suggests that adding the cross-time constraints significantly reduces model fit. However, as the chi-square test is known to be sensitive to large sample sizes, it is useful to also compare fit using approximate measures and information criteria. The constrained model showed a very small reduction in CFI (.018) and no change in RMSEA; moreover, both the AIC and BIC, which weight parsimony in addition to fit, suggested that the constrained model fits better. On the whole, thus, adding the cross-time constraints does not appear to appreciably worsen fit, and the more parsimonious model may improve the generalizability of the results. Thus, we accepted the model with cross-time constraints as our final model.

Figure 5 shows the model with cross-time constraints imposed. Due to these constraints, a single network picture depicts the predictive relations from each measurement occasion to the subsequent occasion. In this figure, paths not significantly different from 0 (*p* > .05) are not shown, nor are auto-regressive paths.

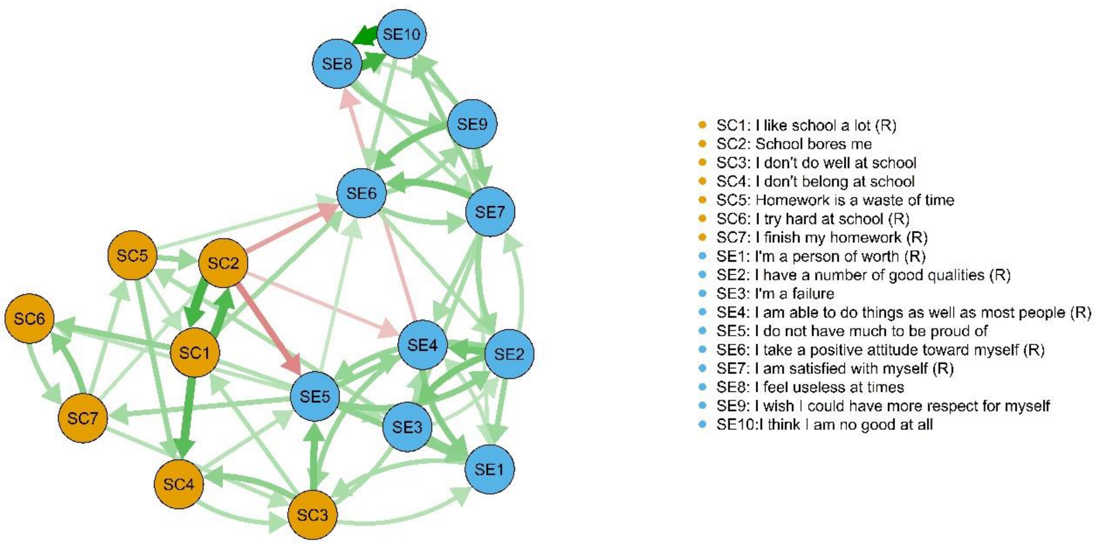

Figure 5. *Estimated CLPN of commitment to school and self-esteem with cross-time constraints imposed. Auto-regressive paths not shown. Paths not significantly different from zero (p > .05) not shown.*

Inspection of Figure 5 reveals several interesting cross-lagged paths – impossible to obtain with a traditional CLPM - that may shed light on the ways in which commitment to school can affect self-esteem and vice-versa. For example, boredom at school (SC2), school performance (SC3), self-worth (SE5), and attitude towards self (SE6) appear to be “bridge nodes” that may connect these two constructs. School performance is predicted by the beliefs that one has worth (SE1) and that one is competent (SE4), and it in turn predicts the belief that one doesn’t have much to be proud of (SE5) and that one is a person of worth (SE1). School performance is also related to other components of commitment to school, for instance by predicting belongingness at school (SC4) and enjoying school (SC1), and being predicted by homework completion (SC7) and belongingness at school (SC4). Self-worth is predicted by school performance (SC3) and boredom at school (SC2) and predicts perceived value of homework (SC5) and effort at school (SC6). A model that treats all of these components as interchangeable markers of a single underlying construct will necessarily miss out on these nuances.

When interpreting the network pathways, it is important to remember that the paths represent conditional predictive relations, controlling for all other variables at the previous measurement occasion. Remembering this can help to interpret counterintuitive-seeming paths, like the significant *negative* paths from finding school interesting (SC2) to positive self-attitude (SE6) and being proud of oneself (SE5): holding constant other variables in the network (e.g., school performance and enjoyment), students who report being bored with school see themselves more positively than those who do not report being bored. While these negative paths appear to contradict the general positive associations among commitment to school variables (e.g., finding school interesting strongly positively predicts and is predicted by enjoyment of school), they might reflect a tendency for students who see themselves as having mastered the material to feel bored in class.

Finally, we note two pairs of variables that have a strong bi-directional influence on each other: Feeling useless (SE8) and thinking of oneself as no good (SE10) and enjoying school (SC1) and being bored by school (SC2). These pairs of items are good candidates for variables that should likely have been collapsed into a single item before fitting the network models. As mentioned earlier, we elected not to collapse any variables because that is best undertaken with expertise in the content domain. But this result suggests what can happen if that step is skipped, namely that associations between each of these nodes and the remainder of the network may be suppressed. For example, the lack of outgoing paths from SE10 to anything else in the network means that, *controlling for SE8,* SE10 had no further significant predictive relation to any other variable. If SE8 and SE10 had been collapsed into a single variable, SE8 would not suppress the estimated influence of SE10[6].

In-prediction and out-prediction indices provide a numerical summary of the influence of individual nodes in the network. We also obtained stability intervals around each of the prediction metrics via bootstrapping. We bootstrapped 800 samples from the original dataset, calculated prediction indices for each of the samples, and then computed the standard deviation of each variable's prediction indices across the bootstrapped samples. The error bars in Figures 6-8 represent +/- one standard deviation around the prediction indices. Figure 6 displays the cross-lagged in-prediction and out-prediction indices for each variable in the CLPN; these indices reveal the extent to which each variable is predicted by (in-prediction) or predicts (out-prediction) all other variables at the previous/subsequent measurement occasion. Figure 7 and Figure 8 display the within-construct and cross-construct versions of these indices, which limit the set of predictors/outcomes to those from within the same construct (within-construct, Figure 7) or to those from the other construct (cross-construct, Figure 8).

Figure 6 shows that belief in one's abilities (SE2) and competence (SE4) are the most highly predictable beliefs (i.e., they have the highest in-prediction). Overall, school competence items tend to have lower in-prediction than self-esteem items. On the other hand, boredom at school (SC2) and believing oneself to be no good (SE10) are the most useful for predicting other variables in the network (i.e., they have the highest out-prediction), but both of these variables have low stability in their out-prediction indices.

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[6] Indeed, we found that, when we collapsed SE08 and SE10 into a single node and re-ran the CLPN analysis, the composite of SE08 and SE10 had more connections than either of the original variables.

Considering within-construct paths only (including the auto-regressive paths; Figure 7), we find that enjoyment of school (SC1), boredom at school (SC2), belief in one's own abilities (SE2), attitude towards yourself (SE6), and satisfaction with self (SE7) are the variables that are best predicted by other within-construct variables. From the stability intervals, we can also see that most of the self-esteem variables have low stability. We also see that enjoying school (SC1), boredom at school (SC2), school performance (SC3), and perception of one's worth (SE10; low stability) are the best predictors of other within-construct variables.

Figure 8 shows the cross-construct prediction indices: Here, we see that the commitment to school variable that can be most reliably predicted *by self-esteem variables* is having a sense of belonging at school (SC4), and the self-esteem variables that can be most reliably predicted by commitment to school variables is the belief in one's competence (SE4) and the feeling of having much to be proud of (SE5)—although SC4 and SE5 have low out-prediction stability. In terms of out-prediction, the most reliable predictor of self-esteem is school performance (SC3; low stability).We can see that there are no reliable cross-construct predictors of commitment to school (all self-esteem variables have low stability and/or small prediction index values). and the most reliable predictors of commitment to school are feeling like no good (SE10)and feeling like one has much to be proud of (SE5).

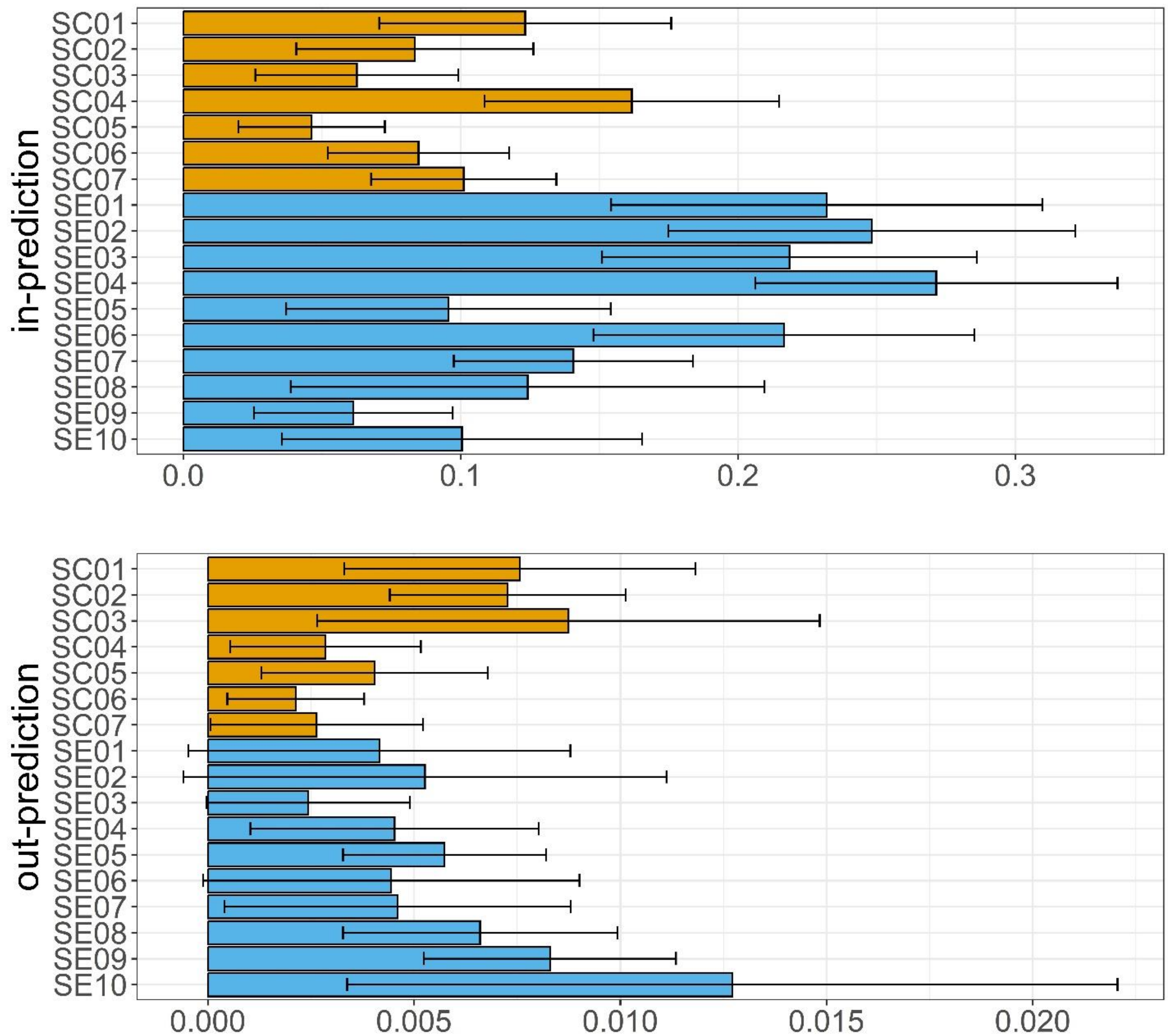

Figure 6. *Cross-lagged in-prediction and out-prediction of variables in the estimated CLPN. Error bars represent -/+ 1 standard error for each of the prediction indices calculated from the bootstrapped samples.*

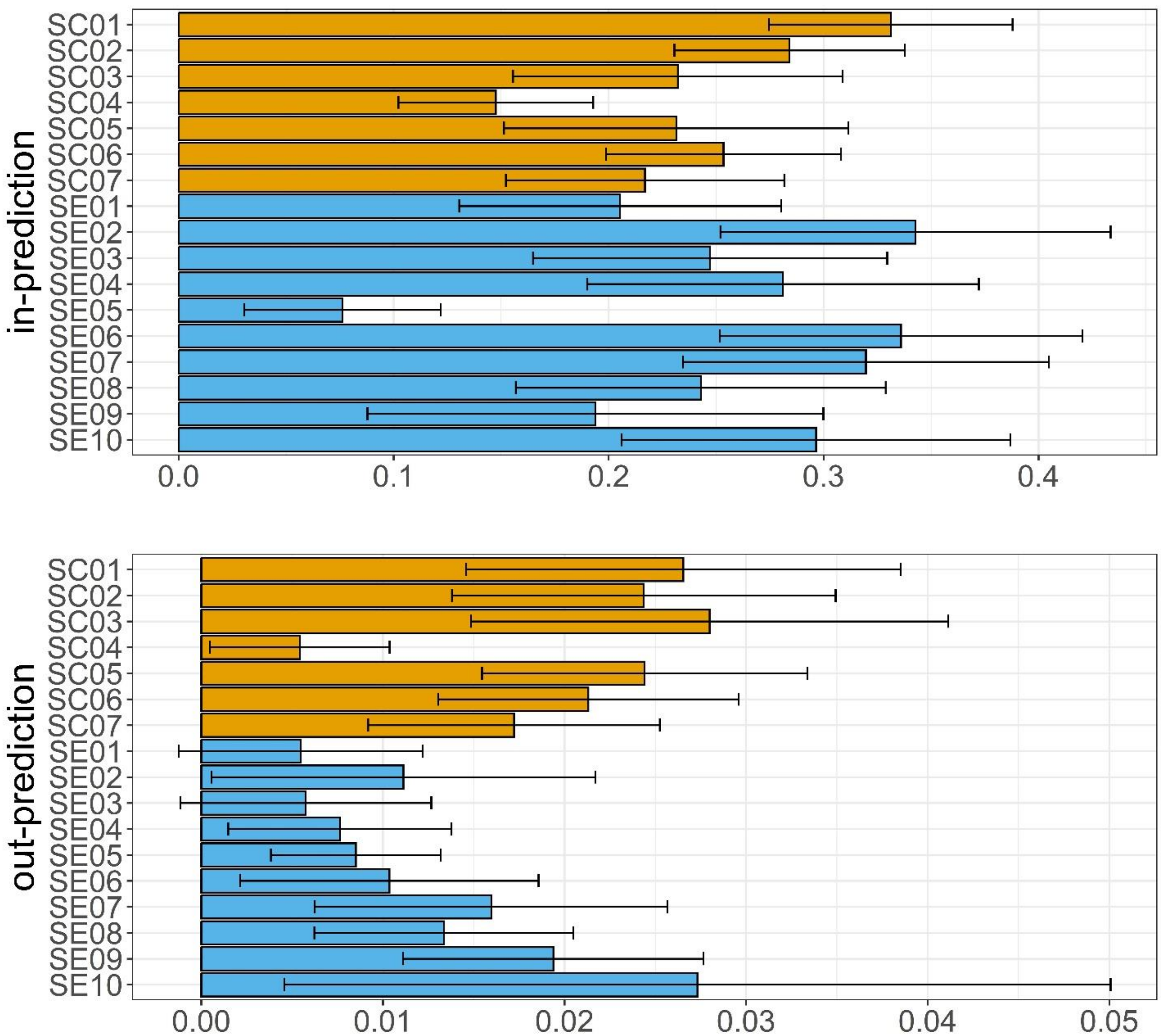

Figure 7. *Within-construct cross-lagged in-prediction and out-prediction of variables in the estimated CLPN. Error bars represent -/+ 1 standard error for each of the prediction indices calculated from the bootstrapped samples.*

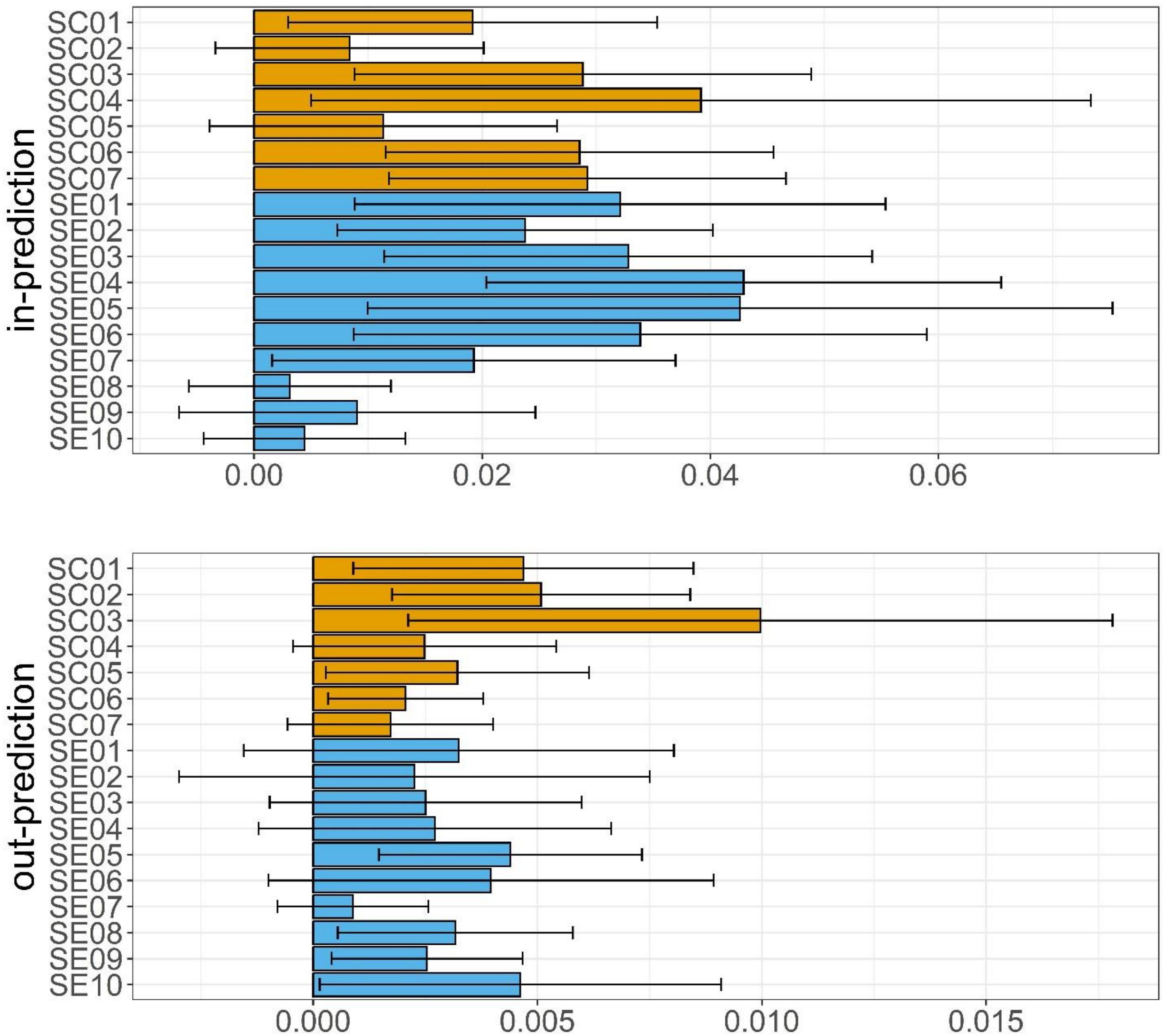

Figure 8. *Cross-construct cross-lagged in-prediction and out-prediction of variables in the estimated CLPN. Error bars represent -/+ 1 standard error for each of the prediction indices calculated from the bootstrapped samples.*

Discussion

In this paper, we proposed a new model for discovering longitudinal predictive effects of psychological constructs on each other based on data from two or more measurement occasions.

The CLPN combines the benefits of latent-variable cross-lagged panel models with the benefits of network representations of psychological constructs to produce a model that can suggest which components of a construct may be responsible for effecting change in another construct, and which components of a construct are most susceptible to change from components of other constructs. The resulting model may reveal not only the extent to which constructs affect each other, but also much more fine-grained detail that could shed light on the relations between the components of the constructs.

To be clear, we do not wish to argue that the CLPN is necessarily a better modeling choice than latent-variable CLPM. Both models may provide interesting findings, and one or the other may be more appropriate for a given set of items. In the example we used here, the latent variable CLPM returned non-significant cross-lagged paths among the latent variables, whereas the CLPN produced many potentially interesting item-level effects. In a situation where items are truly reflective of a single underlying construct, we would expect the CLPM to have greater power to show cross-lagged effects, and for the CLPN to reveal few differential predictive patterns among the items.

Challenges and Extensions

Both the traditional cross-lagged panel model and cross-sectional network models are known to have several limitations that also affect CLPNs. We describe some of the major issues here and consider how they might be dealt with.

Time Lag. Estimated autoregressive and cross-lagged regression paths describe effects at a particular time lag, which may not be appropriate for some or all of the effects under investigation (DeBoeck & Preacher, 2016; Cole & Maxwell, 2003; Gollub & Reichardt, 1987). For example, suppose a researcher wants to study the reciprocal effects of school motivation and school achievement. Suppose further that the motivation → achievement pathway takes days or weeks (e.g., motivation is tied to particular assignments, topics, tests), whereas the achievement → motivation pathway happens on the scale of semesters (e.g., school grades from the previous semester affect motivation in the current semester). If waves of data collection are separated by weeks, the researcher might conclude that motivation affects achievement but not vice versa; if instead waves are separated by semesters, the researcher could conclude the opposite. It is thus essential to choose the time-lag thoughtfully, and to interpret the effects in light of the time-lag represented in the data. A more sophisticated option would be to employ continuous time modeling (Voelkle, Oud, Davidov, & Schmidt, 2012), an approach which, on the assumption that causal effects accrue continuously, produces estimates of causal effects at any arbitrarily chosen time interval. A fruitful future direction for this research would be to extend the CLPN model estimation procedure to allow for estimating the regression parameters in continuous time.

Causation and Mediation. Cross-lagged panel models are frequently used to assess hypotheses about longitudinal mediation effects, but there are two typically untenable assumptions that are necessary to estimate the degree of causal mediation from an indirect path ($X \rightarrow M \rightarrow Y$; Bullock, Green, & Ha, 2010; Fiedler, Schott, & Meiser, 2011; Imai, Keele, & Tingley, 2010; Judd & Kenny, 1981; Pearl, 2012). First, when levels of X are not randomly assigned to participants, it is necessary to evaluate the assumption that, given any observed covariates, X is independent of potential values on M and Y (Imai et al., 2010); which is another way of saying that X is independent of the residuals of M and Y (Bullock et al., 2010). This assumption is untenable whenever any unaccounted-for third variable simultaneously affects levels of X and M, or X and Y.

Second, unbiased estimation of a causal mediation effect requires the assumption that the mediator, *M*, is independent of potential values of the dependent variable, *Y*, given the observed values of *X* and any observed covariates. In other words, *M* is uncorrelated with any other variable that may influence *Y*. Unless both *X* and *M* are experimentally manipulated and randomly assigned, these assumptions are untestable and typically untenable (Bullock et al., 2010; Judd & Kenny, 1981).

In addition to these assumptions, inferring causality from predictive paths also requires that the measurement time-lag corresponds to the timing of the causal effect (see previous section) and that all the variables are measured without error (see "Measurement Error", below). As these assumptions, taken together, are typically impossible to evaluate, it is rarely if ever legitimate to infer causality from cross-lagged coefficients.

While experimental manipulation of *X* and *M* is the best way to ensure that causal mediation conclusions are warranted, many psychological constructs do not allow for experimental manipulation (e.g., neither commitment to school nor self-esteem can be independently manipulated). In such cases, it is recommended to acknowledge these assumptions and to measure as many omitted variables as possible to control for confounders. In addition, Imai et al. (2010) propose a sensitivity analysis that indicates how large the correlation between error terms would have to be for a mediation effect to disappear.

Ergodicity and Within- vs. Between-Subjects Effects. The CLPN model, like any model based on group-level data, relies on the assumption that participants all come from a single population that is described by a single set of dynamic processes. To the extent that the data contain subgroups that are described by different causal patterns, observed effects will reflect a mixture of processes that may describe no actual individuals (Molenaar, 2004). Put another way, the CLPN model relies on between-subjects covariance to infer predictive processes. For these processes to hold at the level of individuals, all individuals must be assumed to be exchangeable draws from a homogeneous population.

A related issue is that CLPN models conflate between-subject and within-subject variance, which can lead to biased model results when the constructs under investigation contain stable individual differences (Hamaker, Kuiper, & Grasman, 2015; Berry & Willoughby, 2017). Hamaker et al. (2015) showed that when stable individual differences exist in the constructs being measured, cross-lagged paths conflate these individual differences (between-subjects effects) with the within-subjects effects that researchers are typically interested in. For example, if some people tend to have higher levels of Self-Esteem than others in general (i.e., if people who have higher than average Self-Esteem at T1 also have higher than average Self-Esteem at T2) and if this stable Self-Esteem trait is correlated with a stable Commitment to School trait, then the CLPM or CLPN will produce positive cross-lagged paths among these correlated variables, even if there is no causal effect within individuals.

Several models have been proposed to disentangle these effects (Hamaker et al., 2015; Grimm et al., 2017), all of which require at least 3 measurement occasions. Hamaker et al.'s random-intercept cross-lagged panel model (RI-CLPM) involves fitting a latent factor to the repeated observations, which has the effect of removing the stable individual differences in levels of the trait. The latent factor accounts for between-subjects effects, leaving the within-subjects effects to be revealed in the auto-regressive and cross-lagged paths. Extending the RI-CLPM model to the CLPN would involve fitting a latent factor to each variable in the network simultaneously to modeling the cross-time paths.

Measurement error. A common criticism of network models is that they do not account for measurement error. Proponents of network models tend to consider this as a feature, rather than a bug: Unlike latent variable models, which equate all unique item variance (reliable and unreliable) with measurement error, network models allow for the reliable unique variance of each item to be a central component of the causal system. As such, networks use the entire variance of each variable to model a construct, rather than just the part that is shared with all other items. However, it is undeniably true that random measurement error also exists, and to the extent that observed scores are unreliable, estimated regression coefficients will be biased. One way to improve this situation would be to include multiple indicators (e.g., self- and partner-report) of each behavior, attitude, emotion, or symptom of interest. Each set of items would then be collapsed (i.e., averaged or summed) into a single score before conducting the CLPN analysis. Such an approach would be expected to result in improved reliability of the observed scores while maintaining the network approach's focus on single behaviors, emotions, attitudes, and symptoms as possessing causal power.

Conclusion

Many researchers have access to longitudinal panel data with two or a few fixed measurement occasions on a few key constructs of interest. To address questions of how these constructs affect each other across the time lag of the study, researchers may consider using the CLPN in addition to, or instead of, the traditional CLPM. The CLPN relies on the insight that many psychological constructs do not function as a single causal entity but, instead, their components may have unique causal force. As such, the effects of one construct on another may be due to particular components of each construct. The CLPN can illuminate these specific relations to reveal nuanced and specific effects, and, as such, generate specific, testable causal hypotheses.

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