Investigating Longitudinal Relationships: A Cross-Lagged Panel Model

Authors: Fang Junyan, Wen Zhonglin, Huang Guomin, Wen Zhonglin

Date: 2022-08-08T00:00:00+00:00

Abstract

Tracking models based on cross-lagged structures play an important role in revealing longitudinal relationships between variables and also lay the foundation for the verification of causal relationships. Cross-lagged panel models can be transformed into other model forms under certain conditions, making the selection of appropriate models an important issue. This paper provides an overview of various models, compares them in terms of model structure, prespecified trajectories, time point requirements, and other aspects, and finally illustrates how to select appropriate models through an example. The results indicate that different models may produce substantially different results in determining variable relationships, and there should be an awareness of model selection and comparison in practical applications.

Full Text

Exploring Longitudinal Relations: Longitudinal Models Based on Cross-Lagged Structure

Junyan Fang[1], Zhonglin Wen[2]*, Guomin Huang[3]

[1] School of Psychology, South China Normal University, Guangzhou, 510631
[2] Center for Studies of Psychological Application / School of Psychology, South China Normal University, Guangzhou, 510631
[3] School of Psychology, South China Normal University, Guangzhou, 510631

*Corresponding author: Zhonglin Wen. E-mail: wenzl@scnu.edu.cn

Abstract

Longitudinal models based on cross-lagged structure are essential for revealing longitudinal relations between variables and provide a foundation for validating causal relationships. The cross-lagged panel model can be transformed into alternative formulations under certain conditions, making model selection a critical consideration. This article provides a comprehensive overview of these models, compares them across dimensions including model structure, presumed trajectories, and time point requirements, and demonstrates the model selection process through an empirical example. Results indicate that different models may produce substantially divergent conclusions regarding variable relations, underscoring the importance of model comparison and selection in applied research.

Keywords: longitudinal relation, cross-lagged, longitudinal model, model selection

1 Introduction

The widespread use of longitudinal designs has stimulated discussion about causal relationships among variables in psychology and other social sciences. Some scholars argue that temporal relationships established from longitudinal data are essentially correlational and insufficient to support reliable causal inferences (Usami et al., 2019); causal inference still requires support from theory, literature, or common sense (温忠麟, 2017). Consequently, researchers investigating variable relationships using longitudinal data more often employ the term longitudinal relation or reciprocal relation rather than causality (Usami et al., 2019; Wiedermann & von Eye, 2020). Longitudinal reciprocal relations represent bidirectional effects, which in empirical research typically manifest as early values of one variable influencing later values (or changes) of another variable, and vice versa (Curran et al., 2014; Wiedermann & von Eye, 2020). Such reciprocal influences are common in psychological research; for instance, theories in developmental psychology generally posit that individual characteristic variables and environmental variables mutually affect each other (Curran et al., 2014). Exploring longitudinal reciprocal relations between variables is crucial for understanding individual development across the lifespan and can lay the foundation for validating causal inferences (Mund & Nestler, 2019).

The Cross-Lagged Panel Model (CLPM) is widely recognized as a powerful method for investigating dynamic relationships between variables. Compared with traditional methods for analyzing repeated measures data, CLPM offers high flexibility in handling time-varying covariates, multivariate analysis, and multi-group analysis, while providing various model fit indices and modification indices (Curran et al., 2010). CLPM reflects diachronic effects between variables through cross-lagged paths, namely by constructing paths from a variable's prior level to its current level (called autoregressive effects) and to the current level of another variable (called cross-lagged effects). A prominent advantage of the cross-lagged structure is its ability to control for the prior level of the outcome variable, thereby controlling for the influence of a potential "third variable" (Cole & Maxwell, 2003).

In longitudinal research, the prior level of an outcome variable is often correlated with both the current value of the outcome and the predictor variable, thus necessitating control for its influence. Building upon the cross-lagged structure, a series of longitudinal models have emerged, including the Random Intercept Cross-Lagged Panel Model (RI-CLPM), Latent Curve Model with Structured Residuals (LCM-SR), and Latent Change Score Model (LCS). These models have been widely applied to investigate longitudinal relations between variables. Different models have their respective strengths and apply to different data structures; no single model is universal (Curran et al., 2014; Mund & Nestler, 2019). However, many researchers do not understand the differences between these models and lack awareness of model selection and comparison in practical applications.

This article analyzes and compares longitudinal models based on cross-lagged structure. We first provide an overview of the aforementioned models, then clarify the differences and associations among them and identify the research contexts to which each model applies, and finally demonstrate how to select an appropriate model through an empirical example.

2.1 Cross-Lagged Panel Model (CLPM)

Jöreskog (1970) integrated the vector autoregressive model from time series analysis into the structural equation modeling framework, giving rise to the CLPM, which assumes that observed values of variables fluctuate around group means.

For variables x and y, the observed values for subject i (i = 1,···,N) at time point t (t = 1,···,T) are x_{it} and y_{it}:

$$x_{it} = {}_{xt} + x_{it}^*$$
$$y_{it} = {}_{yt} + y_{it}^*$$

where ${}_{xt}$ and ${}_{yt}$ represent group means, and x_{it}^* and y_{it}^* represent time-specific deviations. Centering is first performed to extract the time-specific deviations, representing each subject' s temporal fluctuations on the variables:

$$x_{it}^* = x_{it} - {}_{xt}$$
$$y_{it}^* = y_{it} - {}_{yt}$$

The cross-lagged equations are then constructed:

$$x_{it}^* = \beta_{xt} x_{i(t-1)}^* + \gamma_{xt} y_{i(t-1)}^* + d_{xit}$$
$$y_{it}^* = \beta_{yt} y_{i(t-1)}^* + \gamma_{yt} x_{i(t-1)}^* + d_{yit}$$

where β_{xt} and β_{yt} are autoregressive coefficients, γ_{xt} and γ_{yt} are cross-lagged coefficients, and d_{xit} and d_{yit} are regression residuals. The term cross-lagged structure generally refers to the simultaneous inclusion of both autoregressive and cross-lagged paths.

Both autoregressive and cross-lagged coefficients reflect within-subject effects (Curran et al., 2014). Autoregressive coefficients (β{xt}, β{yt}) capture rank-order stability—the property that the relative ordering of subjects on a given variable remains unchanged over time. Cross-lagged coefficients (γ{xt}, γ{yt}) represent the diachronic influence of a predictor variable (e.g., x_i(t-1)*) on an outcome variable (e.g., y_{it}*) after controlling for the effect of the outcome variable' s prior level (e.g., y_i(t-1)*). Cross-lagged coefficients are typically considered key to inferring longitudinal relations between variables.

CLPM assumes the absence of stable between-subject differences, and its parameters confound within-subject and between-subject effects, which may lead to erroneous conclusions (Mund & Nestler, 2019).

2.2 Random Intercept Cross-Lagged Panel Model (RI-CLPM)

Hamaker et al. (2015) introduced latent variables for random intercepts into CLPM, yielding RI-CLPM. This model assumes that observed values of variables fluctuate around individuals' own trait levels.

x_{it} = _{xt} + I_{xi} + x_{it}*
y_{it} = _{yt} + I_{yi} + y_{it}*

Compared with Equation (1), Equation (4) adds trait factors I_{xi} and I_{yi}, representing stable trait factors that vary across individuals. All factor loadings for the trait factors are fixed to 1, also referred to as random intercept terms (Hamaker et al., 2015). After extracting group means and stable trait factors, RI-CLPM similarly employs time-specific deviations (x_{it}*, y_{it}*) to construct the cross-lagged model (same as Equation 3). Compared with CLPM, RI-CLPM more accurately reflects within-subject change processes.

2.3.1 Latent Curve Model (LCM)

The Latent Curve Model with Structured Residuals (LCM-SR) is built upon the Latent Curve Model (LCM), also known as Latent Growth Model (LGM) and Latent Growth Curve Model (LGCM). Proposed by Meredith and Tisak (1990), this model uses observed variables at specific time points to infer the underlying growth trend of variables.

x_{it} = I_{xi} + λt S{xi} + x_{it}*
y_{it} = I_{yi} + λt S{yi} + y_{it}*
I_{xi} = _{xI} + _{xIi}
I_{yi} = _{yI} + _{yIi}
S_{xi} = _{xS} + _{xSi}
S_{yi} = _{yS} + _{ySi}

where I_{xi} and I_{yi} represent the initial values (intercepts) of x and y, S_{xi} and S_{yi} represent rates of change, λt *represents a function of time (e.g., for linear growth models,* $\lambda t = t - 1$, $t \geq 2$); x_{it}^* and y_{it}^* represent residuals, which are independent across time points for the same variable and correlated across variables at the same time point; $_{xI}$ and $_{yI}$ represent the mean initial values across all subjects; $_{xS}$ and $_{yS}$ represent the mean rates of change across all subjects; and $_{xIi}$, $_{yIi}$, $_{xSi}$, $_{ySi}$ represent errors.

The primary purpose of LCM is to characterize features of variable growth trajectories. The intercept and rate of change can be collectively termed growth factors. However, growth factors cannot reflect the within-subject process of co-development between two variables, so here we only consider the Latent Curve Model with Structured Residuals (LCM-SR).

2.3.2 Latent Curve Model with Structured Residuals (LCM-SR)

Proposed by Curran et al. (2014), LCM-SR introduces a cross-lagged structure into LCM, using residuals after extracting growth factors to construct cross-lagged equations. LCM-SR assumes that variables x and y have systematic time-varying trends reflected through growth factors (I_{xi}, I_{yi}; S_{xi}, S_{yi}). The residuals in Equation (5) are first moved to the left side of the equation:

$$x_{it}^* = x_{it} - I_{xi} - \lambda t \, S_{xi}$$
$$y_{it}^* = y_{it} - I_{yi} - \lambda t \, S_{yi}$$

Cross-lagged equations are then constructed to structure the residuals:

$$x_{it}^* = \beta_{xt} \, x_{i(t-1)}^* + \gamma_{xt} \, y_{i(t-1)}^* + d_{xit}$$
$$y_{it}^* = \beta_{yt} \, y_{i(t-1)}^* + \gamma_{yt} \, x_{i(t-1)}^* + d_{yit}$$

In LCM-SR, the growth factors that characterize variable development trajectories do not participate in the cross-lagged equations; the key parameters in the latter are only time-specific, thus clearly separating between-subject differences and within-subject effects (Curran et al., 2014). However, some scholars argue that LCM-SR detrends variables before constructing longitudinal relations equations, excluding the role of growth factors. Therefore, unless there is sufficient reason to believe that variable development trajectories are primarily caused by time-varying omitted variables, using this model may introduce estimation bias (Usami et al., 2019).

2.4 Latent Change Score Model (LCS)

The Latent Change Score Model, also known as Latent Difference Score Model (LDSM), was proposed by McArdle and Hamagami (2001). LCS models based on change scores, focusing on how a variable' s prior level influences another variable' s change.

Unlike the aforementioned models, LCS considers measurement error:

$$x_{it} = f_{xit} + {}_{xit}$$
$$y_{it} = f_{yit} + {}_{yit}$$

where f_{xit} and f_{yit} represent latent scores, and ${}_{xit}$ and ${}_{yit}$ represent measurement errors.

Latent change scores are obtained:

$$\Delta f_{xit} = f_{xit} - f_{xi(t-1)}$$
$$\Delta f_{yit} = f_{yit} - f_{yi(t-1)}$$

where Δf_{xit} and Δf_{yit} represent latent change scores, i.e., the amount of change in the latent variable between time t-1 and t. Cross-lagged equations are then constructed based on latent change scores:

$$\Delta f_{xit} = G_{xi} + \beta_{xt} f_{xi(t-1)} + \gamma_{xt} f_{yi(t-1)} + d_{xit}$$
$$\Delta f_{yit} = G_{yi} + \beta_{yt} f_{yi(t-1)} + \gamma_{yt} f_{xi(t-1)} + d_{yit}$$

where G_{xi} and G_{yi} describe the overall increase or decrease of variables over time, called constant change, while the autoregressive and cross-lagged components represent proportional change. The LCS model can simultaneously investigate long-term changes and immediate fluctuations in variables.

All aforementioned models by default require equally spaced measurement intervals during parameter estimation to ensure meaningful parameter interpretation (Mund & Nestler, 2019).

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3 Model Comparison

The various longitudinal models based on cross-lagged structure are similar in configuration and have certain associations (see Figure 1 [Figure 1: see original paper]). Figure 1 shows the relationships among models. First, certain transformations of CLPM can yield other forms of cross-lagged models. Using CLPM as the baseline model, incorporating trait factors that vary across individuals (I_{xi}, I_{yi}) into the equations yields RI-CLPM; adopting LCM' s approach to extract growth factors (I_{xi}, I_{yi}; S_{xi}, S_{yi}) and then building cross-lagged paths based on residuals yields LCM-SR; not centering observed values but considering measurement error (as in Equation 9), then using differences in latent scores to build cross-lagged paths and adding constant change factors that vary across individuals (G_{xi}, G_{yi}) yields LCS (Usami et al., 2015). Therefore, LCM-SR, RI-CLPM, and LCS can be considered special forms of CLPM under certain transformations.

These models also have mathematical associations. Usami et al. (2019) summarized a unified structural framework consisting of three general equations: measurement equation, decomposition equation, and dynamic equation. Assuming that autoregressive and cross-lagged coefficients do not vary over time, the three equations are respectively:

x_{it} = f_{xit} + _{xit}, y_{it} = f_{yit} + _{yit} (12)
f_{xit} = _{xt} + I_{xi} + (t - 1)S_{xi} + f_{xit}, *f_{yit} = _{yt} + I_{yi} + (t - 1)S_{yi} + f_{yit}* (13)
f_{xit}* = G_{xi} + *βx f*{xi}(t-1) + *γx f*{yi}(t-1) + d_{xit}, f_{yit}* = G_{yi} + *βy f*{yi}(t-1) + *γy f*{xi}(t-1) + d_{yit} (14)

Note that to comprehensively encompass all models, measurement error is considered in the measurement model by introducing latent scores (f_{xit}). Therefore, to maintain consistency in symbols on both sides of the subsequent decomposition equation, f_{xit}* and f_{yit}* are used to represent time-specific deviations or residuals, corresponding to x_{it}* and y_{it}* in equations like (1).

By deleting and retaining specific elements in the three general equations, different cross-lagged models can be obtained. For example, deleting measurement error (_{xit}) in the measurement equation, deleting intercept and rate-of-change factors ([I_{xi} + (t - 1)S_{xi}]) in the decomposition equation, and retaining only the cross-lagged structure and residuals ([*βx f*{xi}(t-1) + *γx f*{yi}(t-1) + d_{xit}]) in the dynamic equation yields CLPM. Based on CLPM, retaining intercept factors (I_{xi}) in the decomposition equation yields RI-CLPM. Based on CLPM, deleting means (_{xt}) but retaining intercept and rate-of-change factors ([I_{xi} + (t - 1)S_{xi}]) in the decomposition equation yields LCM-SR. Based on CLPM, retaining measurement error (_{xit}) in the measurement equation, deleting means, intercept factors, and rate-of-change factors ([_{xt} + I_{xi} + (t - 1)S_{xi}]) in the decomposition equation, and retaining constant change factors (G_{xi}) yields LCS (since LCS is based on differences, its autoregressive coefficient should be *β*_x' = 1 + *β*_x).

Furthermore, some scholars have demonstrated certain mathematical associations between univariate LCM and LCS and provided parameter conversion formulas under different forms. For example, for a univariate LCM satisfying linear growth assumptions, the mean and variance of its intercept (I_{xi}) equal the mean and variance of the latent score (f_{xi}(t=1)) at time t=1 in the univariate constant-change LCS, while the mean and variance of its rate of change (S_{xi}) correspond to the mean and variance of the constant change factor (G_{xi}) in LCS: _{Ix} = _{fx}(t=1), _{Sx} = *σ{fx}(t=1)^2, σ*{Sx}^2 = *σ*_{Gx}^2 (Serang et al., 2019).

Despite structural similarities, significant differences exist among these models, which may lead to markedly different analytical results and interpretations.

Table 1 summarizes the differences among the four cross-lagged longitudinal models discussed in this article, detailed as follows.

First, the modeling objects differ. CLPM uses centered variables, i.e., extracting the mean at each time point (in Mplus this is done by defining latent variables with all loadings fixed to 1). RI-CLPM uses variables after extracting both means and trait factors. LCM-SR uses detrended variables, i.e., after extracting intercept and rate-of-change factors. LCS builds cross-lagged structure based on change values of latent variables between different time points.

Second, the presumed trajectories differ. LCM-SR is primarily used to analyze variables with linear or nonlinear developmental trajectories and can provide information about characteristics of variable growth trajectories. LCS can analyze variables satisfying exponential developmental trajectories (Mund & Nestler, 2019). The other two models cannot explicitly provide such information.

Third, the decomposition of within-subject and between-subject effects differs. Cross-sectional designs can only obtain between-subject effect data, whereas longitudinal data can reflect both between-subject differences and within-subject processes. Distinguishing these two effects is crucial for understanding the nature of longitudinal relations between variables. CLPM and LCS do not model between-subject difference components nor distinguish between-subject differences and within-subject processes (Curran et al., 2014; Mund & Nestler, 2019), whereas RI-CLPM and LCM-SR distinguish between-subject differences by separating the influence of trait factors (e.g., I_{xi}) and growth factors (e.g., I_{xi}, S_{xi}), respectively. If there is sufficient reason to believe that between-subject differences are non-negligible in the co-development process of variables, researchers should select models that can distinguish within-subject and between-subject effects to obtain true variable interrelations.

Fourth, the models have different requirements for the number of time points in longitudinal data. Usami et al. (2019) note that under stability assumptions (i.e., autoregressive and cross-lagged coefficients do not vary over time), CLPM requires at least two repeated measurements, while other cross-lagged models require at least three.

Fifth, the models apply to different research contexts. For example, if one variable does not have a systematic change trend (e.g., y is reading achievement while x is number of absenteeism days in a school year), LCM-SR with its presumed developmental trajectory would be inappropriate.

Thus, although different models have certain associations, each model applies to different contexts and provides different information about variable development (Parker et al., 2015). Therefore, in practical applications, model comparison and selection are necessary in the absence of clear theoretical prescriptions.

4 Empirical Example

We now use an empirical example to illustrate the differences in analytical results obtained when different cross-lagged longitudinal models are applied to the same dataset. The data come from the open-access database of the China Family Panel Studies (CFPS). We aim to explore the longitudinal relationship between subjective well-being and Body Mass Index (BMI). Subjective well-being was measured by a single questionnaire item asking subjects to rate their current life on a scale from 1 (very poor) to 5 (very good). BMI was calculated from self-reported or proxy-reported height and weight data: BMI = weight (kg) / height (cm)^2. Three time points were selected (T1 = 2014, T2 = 2016, T3 = 2018). Outliers were removed, and only subjects with records at all three time points were retained, yielding valid data from 1,525 subjects. The mean age at the initial time point was 20 years (range 16-71), and 49% were male.

Mplus 8.0 software was used for analysis (see Appendix). The primary purpose here is model comparison, so full models assuming longitudinal reciprocal relations between variables were used, and the same type of autoregressive and cross-lagged coefficients were constrained to be time-invariant. Additionally, given that LCM-SR presumes growth trajectories, univariate LCM analyses were first conducted for each variable.

Results indicated that both variables exhibited systematic temporal trends: I_{well}-being = 3.80 ($p < 0.001$), S_{well}-being = 0.01 ($p < 0.05$), I_{BMI} = 20.88 ($p < 0.001$), S_{BMI} = 0.08 ($p < 0.001$), making them suitable for subsequent analysis.

Model fit results for different models are shown in Table 2 . When fit indices meet the following criteria: RMSEA less than 0.08, SRMR less than 0.08, CFI greater than 0.90, and TLI greater than 0.90, the model can be considered to fit the data well (温忠麟等, 2004). As can be seen, LCM-SR fit poorly, while the other models showed good overall fit.

Parameter estimation results for different models are presented in Table 3 . For the same longitudinal dataset, each model provides different types of parameter information. First, regarding variable development trajectories, LCM-SR results indicated that BMI had a significant linear growth trend with significant intercept and rate-of-change factors, while the rate-of-change factor for subjective well-being was not significant. Second, regarding autoregressive effects, both CLPM and RI-CLPM showed that both variables exhibited some rank-order stability, but the degree of stability reflected by each model differed. LCM-SR only identified rank-order stability for BMI. Due to model complexity, LCS produced some improper solutions after standardization (Usami et al., 2019). Finally, regarding cross-lagged effects, CLPM, RI-CLPM, and LCM-SR all identified diachronic influences between variables, but the direction of effects differed. CLPM results indicated that BMI had a significant diachronic influence on subjective well-being, i.e., prior BMI positively influenced subsequent subjective well-being. In contrast, RI-CLPM results indicated that prior subjective well-being had a significant negative influence on subsequent BMI, while LCM-SR results indicated that prior BMI negatively influenced subsequent subjective well-being.

These results demonstrate that when analyzing the same dataset, different models yield somewhat different parameter estimates because they have different compositions and underlying assumptions. On one hand, some models may be inappropriate for the data; for example, LCM-SR showed poor model fit, suggesting it may not accurately capture the true variable relationships underlying the data. On the other hand, because models differ in composition, parameters may reflect different effects. For instance, CLPM is believed to confound between-subject and within-subject processes, so its parameter results may not truly reflect reciprocal relations between variables. In contrast, RI-CLPM separates between-subject differences by extracting stable trait factors, and its estimates can more accurately reflect dynamic interactions between variables.

Except for LCM-SR, all other models showed good fit. Model determination cannot rely solely on fit indices; model characteristics and relevant theoretical background must also be considered. First, research indicates that both subjective well-being and BMI exhibit significant between-subject differences (Bieda et al., 2019; Pereira & Coelho, 2013), so CLPM was excluded. Additionally, LCM-SR' s poor fit suggested it was unsuitable for capturing the variable relationships under investigation. Finally, since this study' s focus was not on change scores and LCS was overly complex leading to improper solutions, LCS was excluded. In summary, RI-CLPM was selected as the final model, leading to the conclusion: at the between-subject level, subjective well-being and BMI showed a significant positive correlation ($r = 0.26$, $p < 0.05$), indicating that subjects with higher subjective well-being tended to have higher BMI, 正所谓心宽体胖 (as the saying goes, "a contented mind leads to a contented body"). At the within-subject level, both variables showed some rank-order stability, with subjective well-being showing lower stability (0.15 ~ 0.18) and BMI showing higher stability (0.52 ~ 0.60). Regarding diachronic influences between the two variables: prior BMI negatively influenced subsequent subjective well-being (γ{BMI}→well-being = -0.05 ~ -0.07, $p > 0.05$), but not significantly; prior subjective well-being negatively influenced subsequent BMI (γ{well}-being→BMI = -0.05 ~ -0.06, $p < 0.05$), but the effect was small.

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5 Discussion

Emerging longitudinal models often employ cross-lagged paths to investigate diachronic effects between variables; therefore, these models share structural similarities. However, subtle differences may lead to divergent analytical results, particularly in judging directional influences between variables, potentially yielding statistically different or even opposite conclusions. Thus, selecting an appropriate model is essential.

Researchers need to understand the applicable contexts of different longitudinal models, develop awareness of model comparison and selection, and gradually establish standardized procedures for longitudinal research.

First, during the research design phase, adequate sample size and number of time points should be ensured, with attention to controlling measurement intervals. Generally, equally spaced designs are recommended to facilitate meaningful interpretation of results.

Second, during the data analysis phase, candidate models can be considered based on data characteristics (e.g., number of time points). Multiple models can help obtain rich information about variable development (Parker et al., 2015).

Finally, model selection should be made through comprehensive comparison, considering: (1) research purpose. If researchers aim to characterize development trajectories, LCM or LCM-SR is preferred; if the aim is to analyze longitudinal interaction mechanisms between variables, LCM-SR, CLPM, RI-CLPM, or LCS can be chosen. (2) theoretical background or empirical evidence. If evidence indicates that between-subject differences should be separated from within-subject processes, LCM-SR or RI-CLPM would be more appropriate. (3) model fit. Researchers can utilize various fit indices for model selection.

Longitudinal models based on cross-lagged structure focus on diachronic effects between variables and can provide multiple types of information about variable development and change. They play an important role in revealing longitudinal relations and can provide evidence for 论证 causal relationships between variables. Conducting model comparison based on practical background, research purpose, and statistical results helps build appropriate longitudinal models.

This article only demonstrates full models for bivariate longitudinal models. In actual analysis, researchers can also simplify full models to unidirectional models or relax stability assumptions, and can incorporate time-varying or time-invariant covariates for further in-depth analysis. The several models described in this article have been widely discussed and applied in theoretical and empirical research. Additionally, other cross-lagged models exist, such as the Factor-Cross Lagged Panel Model (factor-CLPM) (McArdle, 2009), Stable Trait Autoregressive Trait and State Model (STARTS) (Kenny & Zautra, 2001), and Multi-level Cross-Lagged Model (Yu et al., 2015). Future research could incorporate these models for more systematic comparison.

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Appendix: Mplus Syntax

```
Data: FILE = 1.dat;
Variable: names = x1 x2 x3 y1 y2 y3;

Analysis: ESTIMATOR=ML;

!CLPM model:
! define latent variables
etax1 by x1@1;etax2 by x2@1;etax3 by x3@1;
etay1 by y1@1;etay2 by y2@1;etay3 by y3@1;

! autoregressions
etax2 on etax1 (a1);etax3 on etax2 (a1);
etay2 on etay1 (a2); etay3 on etay2 (a2);

! crosslagged paths
etay2 on etax1 (c1);etay3 on etax2 (c1);
etax2 on etay1 (c2);etax3 on etay2 (c2);

! variance structure
etax1;etay1;etax1 with etay1;
etax2-etax3 (e1);etay2-etay3 (e2);
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etax2 with etay2 (cove);etax3 with etay3 (cove);
x1-x3;y1-y3;

! mean structure
[etax1-etax3];[etay1-etay3];
[x1-x3@0]; [y1-y3@0];

!RI-CLPM model:
ix by x1@1 x2@1 x3@1;
iy by y1@1 y2@1 y3@1;
etax1 by x1@1;etax2 by x2@1;etax3 by x3@1;
etay1 by y1@1;etay2 by y2@1;etay3 by y3@1;

etax2 on etax1 (a1);etax3 on etax2 (a1);
etay2 on etay1 (a2);etay3 on etay2 (a2);
etay2 on etax1 (c1);etay3 on etax2 (c1);
etax2 on etay1 (c2);etax3 on etay2 (c2);

x1-x3@0;y1-y3@0;
etax1-etax3;etay1-etay3;
ix; iy; ix with iy;
etax1 with ix@0; etay1 with ix@0;
etax1 with iy@0; etay1 with iy@0;
etax1 with etay1;
etax2 with etay2 (e1); etax3 with etay3 (e2);
[x1-x3@0]; [y1-y3@0];
[etax1-etax3@0]; [etay1-etay3@0];
[ix iy];

! LCM Model:
i1 s1 | x1@0 x2@1 x3@8 ;
i2 s2 | y1@0 y2@1 y3@2 ;
s1 with i2; s2 with i1;

!LCM-SR model:
ix by x1@1 x2@1 x3@1 ;
sx by x1@0 x2@1 x3@2 ;
iy by y1@1 y2@1 y3@1 ;
sy by y1@0 y2@1 y3@2 ;

etax1 by x1@1; etax2 by x2@1; etax3 by x3@1;
etay1 by y1@1; etay2 by y2@1; etay3 by y3@1;

etax2 on etax1 (a1); etax3 on etax2 (a1);
etay2 on etay1 (a2); etay3 on etay2 (a2);
etay2 on etax1 (c1); etay3 on etax2 (c1);
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etax2 on etay1 (c2); etax3 on etay2 (c2);

x1-x3@0; y1-y3@0;
etax1-etax3; etay1-etay3;
etax1 with etay1;
etax2 with etay2 (e1); etax3 with etay3 (e1);
ix; iy; sx; sy;
ix with sx iy sy; sx with iy sy; iy with sy;
etax1 with ix@0; etax1 with sx@0; etax1 with iy@0; etax1 with sy@0;
etay1 with ix@0; etay1 with sx@0; etay1 with iy@0; etay1 with sy@0;
[x1-x3@0];    [y1-y3@0];
[etax1-etax3@0]; [etay1-etay3@0];
[ix iy]; [sx sy];

model:
etax1 by x1@1; etax2 by x2@1; etax3 by x3@1;
etay1 by y1@1; etay2 by y2@1; etay3 by y3@1;
dx2 by etax2@1; dx3 by etax3@1;
dy2 by etay2@1; dy3 by etay3@1;
gx by dx2-dx3@1; gy by dy2-dy3@1;

etax2 on etax1@1;etax3 on etax2@1;
etay2 on etay1@1;etay3 on etay2@1;

dx2 on etax1 (p1); dx3 on etax2 (p1);
dy2 on etay1 (p2); dy3 on etay2 (p2);
dy2 on etax1 (c1); dy3 on etax2 (c1);
dx2 on etay1 (c2); dx3 on etay2 (c2);

x1-x3 (ux); y1-y3 (uy);
etax2-etax3@0;etay2-etay3@0;
dx2-dx3@0; dy2-dy3@0;
etax1; etay1; gx;gy;
etax1 with etay1; gx with etax1; gx with etay1;
gy with etax1; gy with etay1; gx with gy;
[x1-x3@0]; [y1-y3@0];
[etax2-etax3@0]; [etay2-etay3@0];
[dx2-dx3@0]; [dy2-dy3@0];
[etax1 etay1]; [gx gy];

OUTPUT: STDYX;
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English Abstract

Exploring the longitudinal relations: Based on longitudinal models with cross-lagged structure

Junyan Fang[1], Wen Zhonglin[2], Huang Guomin[3]

[1] School of Psychology, South China Normal University, Guangzhou, 510631
[2] Center for Studies of Psychological Application / School of Psychology, South China Normal University, Guangzhou, 510631
[3] School of Psychology, South China Normal University, Guangzhou, 510631

A cross-lagged structure usually consists of two kinds of effects, autoregressive effects of the prior level of a variable on the current level of itself and cross-lagged effects of the prior level of one variable on the current level of another variable. Longitudinal models with the cross-lagged structure are well recognized as powerful techniques for revealing longitudinal relations between two variables and laying the foundation of diachronic causation. There exist several cross-lagged longitudinal models, while practitioners know little about the association and difference among them, which makes it difficult to choose the most proper one. Although these models are similar in structure, they may differ in the results of estimation. Thus, it is necessary to get a whole picture of these longitudinal models and learn how to compare and choose among them. The present study aims to analyze different cross-lagged longitudinal models and compare them, so as to reveal the importance of model comparison and model selection and provide strategies to select among models.

First, we introduce four popular longitudinal models with cross-lagged structure: Cross-Lagged Panel Model (CLPM), Random-Intercept Cross-Lagged Panel Model (RI-CLPM), Latent Curve Model with Structured Residuals (LCM-SR), and Latent Change Score Model (LCS). Then, we clarify the similarities and associations among them. Next, we discuss their differences in various aspects. Finally, we conduct an empirical study to illustrate the procedure of model selection.

Results show that: (1) these models are very similar in the model configuration because they all analyze diachronic relations by the cross-lagged structure; (2) CLPM can transform into RI-CLPM, LCM-SR and LCS under certain conditions; (3) different models focus on different developmental characteristics and each of them can provide valuable information on the change process; (4) these models could give different estimation results when applied to the same data set, which may induce different conclusions.

We summarize several reference points for selecting a proper longitudinal model in practice: (1) research purpose. If researchers are interested in characterizing the development trajectories, then LCM or LCM-SR is preferred; (2) theoretical knowledge and empirical experience. If there is sufficient evidence showing that the within-person process should be separated from between-person difference, then LCM-SR and RI-CLPM could be considered; (3) the model fitting. Several model fit indices can be used.

In summary, longitudinal models with cross-lagged structure play an important role in revealing longitudinal relations between psychological constructs. These models are similar in configuration but vary in modeling basis, premises and data requirements, which may give rise to distinct estimation results and conclusions. Researchers should understand the association and differences among them with considerable insight into model comparison and model selection. It is advisable to try different reasonable models and choose the most proper one for the exploration of longitudinal relations.

Keywords: longitudinal relation, cross-lagged, longitudinal model, model selection