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Temporal Misalignment in Intensive Longitudinal Data: Consequences and Solutions Based on Dynamic Structural Equation Models

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ABSTRACT

Intensive longitudinal data has been widely used to examine reciprocal or causal relations between variables. However, these variables may not be temporally aligned. This study examined the consequences and solutions of the problem of temporal misalignment in intensive longitudinal data based on dynamic structural equation models. First the impact of temporal misalignment on parameter estimation were investigated in a simulation study, which showed that temporal misalignment led to incomparable cross-lagged effects between variables. Then, two solutions, model adjustment and data interpolation, were proposed, and their performance was compared with those of the naive estimation which blindly treating temporally misaligned data as aligned. The simulation results supported the effectiveness of the model adjustment method over the other two methods. Finally, all three methods were applied to two empirical data collected by daily diaries and empirical sampling method, and recommendations were made for collecting and analyzing intensive longitudinal data.

KEYWORDS

Cross-lagged; daily diary; dynamic structural equation model; ecological momentary assessment; intensive longitudinal data; temporal misalignment

1. Introduction

Intensive longitudinal data (ILD) has been increasingly used in social and behavioral science (Hamaker & Wichers, 2017). It is commonly collected through daily diaries (Bolger et al., 2003), experience sampling method (ESM; Hektner et al., 2007), and ecological momentary assessment (EMA; Smyth & Stone, 2003). These methods measure people's feelings and performance in normal life and have been widely used in the last decade due to their high ecological validity and low recall bias (Trull & Ebner-Priemer, 2014). One popular modeling approach for intensive longitudinal data is dynamic structural equation modeling (DSEM), which is developed based on structural equation modeling (SEM), multilevel modeling (MLM), and time-series analysis (Asparouhov et al., 2018; McNeish & Hamaker, 2020). It has been used to examine the bidirectional relation between various variables such as positive and negative affect (Hamaker et al., 2018; Simons et al., 2021); exam-related emotions and regulation strategies (Rottweiler & Nett, 2021); achievement goals and academic success (Neubauer et al., 2022); nighttime sleep and sedentary behavior of toddlers (Armstrong et al., 2019); and daily hassles and physical health complaints (Tran et al., 2021).

With the widespread use of ILD, the problem of time-interval dependency has attracted much attention (Gollob & Reichardt, 1987; Hecht & Zitzmann, 2021; Kuiper & Ryan, 2018; McNeish & Hamaker, 2020). This problem is twofold. First, if the time intervals between all repeated measurements are equal, the estimated parameters (e.g., cross-lagged parameters) will be a function of the time interval between measurement occasions (Hecht & Zitzmann, 2021), suggesting that the estimated effects (e.g., cross-lagged effects) are subject to the length of time interval set in the study. Furthermore, if the intervals are not equal, the estimated parameters will be biased because the repeated measures will be treated as if they are equally spaced. In the framework of discrete-time modeling, the problem of unequal time intervals can be addressed by using DSEM, as it allows researchers to rescale measurements and automatically fill in unobserved time points, and then apply a Kalman filter to predict unobserved data (McNeish & Hamaker, 2020).

However, another issue related to the timing of repeated measurements in intensive longitudinal data—the problem of temporal misalignment—has been understudied. As shown in Figure 1, there are two main types of temporal misalignment in intensive longitudinal data, which are caused by different reasons. The first type of temporal misalignment (see Figure 1a) occurs when the two variables are not measured at the same time, which is due to the inherent differences in the timing of the variables (Armstrong et al., 2019; Neubauer et al., 2021; Neubauer et al., 2022). This situation is particularly common in studies that focus on the relations between variables that occur at different times of the day (e.g., day and night). For example, suppose a researcher conducted a daily diary study to investigate the bidirectional relation between negative affect during the day (Y_1) and sleep quality at night (Y_2). Participants reported on their negative affect during the day each evening and their sleep quality the next morning. The temporal difference

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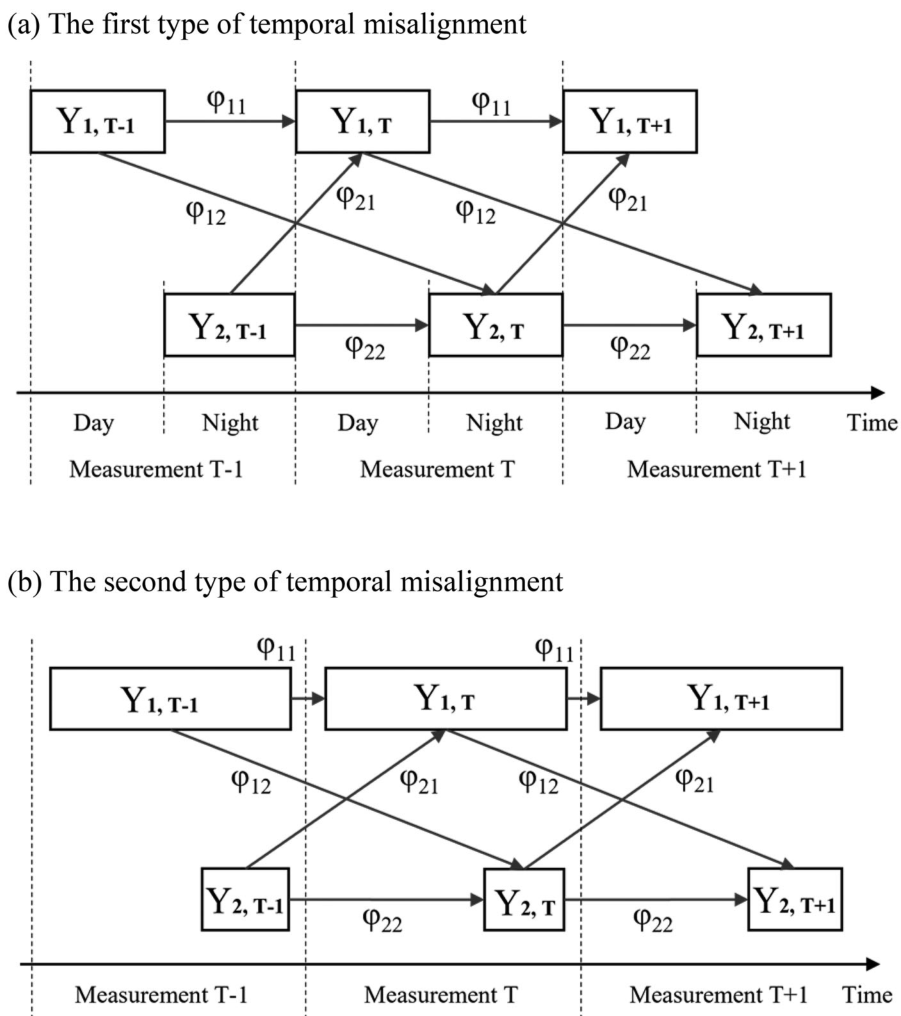

Figure 1. Two main types of temporal misalignment. Y_1 and Y_2 are two temporally misaligned variables. φ_{11} and φ_{22} denote autoregressive parameters, and φ_{12} and φ_{21} denote cross-lagged parameters.

between negative affect and sleep quality resulted in the temporal misalignment between these two variables.

The second type of temporal misalignment (see Figure 1b) occurs when the variables are measured at the same time, but the time ranges of the variables do not correspond (Blanke et al., 2022; Luo et al., 2022). The main difference between this type and the previous one is that the variables in this situation can occur simultaneously. The reason why the variables are temporally misaligned is usually due to the different time references used to measure the variables. For example, in an ecological momentary assessment study, researchers were interested in the bivariate relation between eating behavior (Y_1) and stress (Y_2). These two variables were measured at certain time intervals (e.g., 4 h) during the day. Participants reported the total amount of food consumed since they completed the last questionnaire, and their stress level at the time of completing the current questionnaire. The different time references (i.e., "since you completed the last questionnaire" and "at this moment") used to measure the two variables resulted in the temporal misalignment between these two variables. In addition, it is worth noting that although the causes of these two types of temporal misalignment are different, their data patterns are essentially the same.

Then what are the consequences of temporal misalignment between variables? Researchers who collect intensive longitudinal data may be interested in how changes in one variable affect subsequent changes in another variable (Hecht & Zitzmann, 2021; Usami et al., 2019), and this can be explored through the cross-lagged effects estimated in DSEM. However, inferring the cross-lagged relation between variables can be problematic if the variables of interest are not temporally aligned. As revealed in Figure 1, when researchers blindly fit temporally misaligned data to a DSEM, the time interval corresponding to the cross-lagged effect of Y_1 (e.g., eating behavior in Figure 1b) on Y_2 (e.g., stress in Figure 1b) is much larger than that of Y_2 on Y_1. In this case, if it turns out that the predicting effect of the current stress (i.e., $Y_{2,\ T}$) on the eating behavior during the next period (i.e., $Y_{1,\ T+1}$) is much larger than that of the eating behavior during the previous period (i.e., $Y_{1,\ T}$) on the subsequent stress (i.e., $Y_{2,\ T+1}$), we cannot discern whether this is due to a truly stronger cross-lagged effect of stress on eating behavior or to the shorter time interval corresponding to this effect. In other words, the cross-lagged relations between temporally misaligned variables (e.g., stress and eating behavior) are incomparable, making it impossible to make reasonable inferences about their reciprocal influence or causal relations. In addition, the estimation of the autoregressive effects of the variables may also be affected by the temporal misalignment between variables, because the path coefficients in DSEM were estimated based on the covariance matrix of the variables, and biased estimates of the cross-lagged parameters may also lead to biased estimates of the autoregressive parameters. Therefore, temporal misalignment between variables may have a negative impact on the estimation of both the autoregressive effects of variables and the cross-lagged effects between variables.

The main objective of this study is to examine the consequences and solutions of the temporal misalignment between variables in intensive longitudinal data based on DSEM. Four studies were included in this article. In Study 1, we simulated intensive longitudinal data with different degrees of temporal misalignment, and explored the influence of temporal misalignment on parameter estimation by blindly treating temporally misaligned data as aligned. In Study 2, we first proposed two possible solutions, the model adjustment method and the data interpolation method, and then compared the parameter estimation results of these two solutions with those of the naïve estimation (i.e., a direct estimation method that blindly treats temporally misaligned data as aligned) to test the effectiveness of the proposed solutions. In Study 3 and Study 4, we illustrated the differences in the results and conclusions of different methods (i.e., naïve estimation, model adjustment, and data interpolation) using two empirical data collected by daily diaries and empirical sampling method, respectively.

2. Study 1: Consequences of Temporal Misalignment

2.1. Methods

2.1.1. Study Design

To examine the consequences of temporal misalignment in intensive longitudinal data, we first simulated data with two variables (i.e., Y_1 and Y_2) that were temporally misaligned to varying degrees. Specifically, to simulate data with T time points per subject, we first generated data with $n \times T$ time points per subject, where n denotes the number of degrees of misalignment. Then, we adjusted the original data by retaining only T time points per subject at some degree of temporal misalignment and finally obtained n sets of adjusted data with different degrees of temporal misalignment.

As shown in Figure 2, we set six degrees of temporal misalignment (i.e., 0, 1/6, 2/6, 3/6, 4/6, 5/6). In Figure 2a, two variables are aligned in time (i.e., degree of temporal misalignment = 0), which is the baseline condition. In Figure 2b, two variables are moderately misaligned in time (i.e., degree of temporal misalignment = 3/6). The autoregressive and cross-lagged parameters of the temporally misaligned data can be compared with those in the baseline condition.

Notably, if we generated data by setting all four parameters (i.e., two autoregressive parameters and two cross-lagged parameters) to the same value (i.e., a), the expected value of the autoregressive and cross-lagged parameters (i.e., $\Phi^{(n)}$) of the adjusted data in the baseline condition were equal and can be calculated by the following formula (See Online Supplementary Material A for the derivation).

$$\Phi^{(n)} = 2^{n-1}a^n. \tag{1}$$

In Study 1, we set $n = 6$, $a = 0.4$; therefore, the autoregressive and cross-lagged effects in the baseline condition should be equal to $2^5 \times 0.4^6 = 0.131$.

2.1.2. Procedure

The original data of two variables were simulated based on DSEM in M*plus* 8.3 (Muthén & Muthén, 2017). M*plus* syntax for data simulation can be found in Appendix A. We set sample size $N = 200$, the number of time points per subject $n \times T = 6 \times 50 = 300$. At the within level, all autoregressive and cross-lagged effects were set to 0.4, the variances of Y_1 and Y_2 were set to 0.7, and the correlation between residuals of Y_1 and Y_2 was set to 0.1. At the between level, the variances of Y_1 and Y_2 were set to 1, and the correlation between Y_1 and Y_2 was set to 0.4. Notably, in our simulation studies, the sample size (i.e., $N = 200$; Armstrong et al., 2019; Rottweiler & Nett, 2021) and the number of time points per subject (i.e., $T = 50$; Xu & Zheng, 2022) were chosen based on common study designs for studies using DSEM. The autoregressive and cross-lagged effects were set based on parameter estimates commonly found in studies using DSEM across multiple domains, including clinical (Gómez Penedo et al, 2021; Johnson et al., 2020; Santangelo et al, 2020; Zhu et al., 2022), health (Armstrong et al., 2021; Kramer et al., 2022), developmental (Armstrong et al., 2019; Borairi et al., 2023; Xu & Zheng, 2022), and educational domains (Neubauer et al., 2022; Niepel et al., 2022; Rottweiler & Nett, 2021). Similarly, the within-person (residual) variances were set based on common empirical results for bivariate DSEMs (Blanke et al., 2022; Gómez Penedo et al, 2022; Niepel et al., 2022). The contemporaneous correlations between variables (i.e., correlations between residuals) at the within-person level were set to be similar to the strength of autoregressive and cross-lagged effects, and at the between-person level, the two variables were set to be moderately correlated (i.e., 0.3–0.5). The simulation was replicated for 500 times.

Then, we retained T time points per subject to manipulate the degree of temporal misalignment of the two variables and obtained six sets of adjusted data. Finally, each set of adjusted data was fitted directly to DSEM without considering temporal misalignment (i.e., naïve estimation). The model estimation process was replicated for 500 times for each set of data using the R package *MplusAutomation* (Hallquist & Wiley, 2018).

To show the influence of temporal misalignment on the accuracy of parameter estimation, we computed the mean of

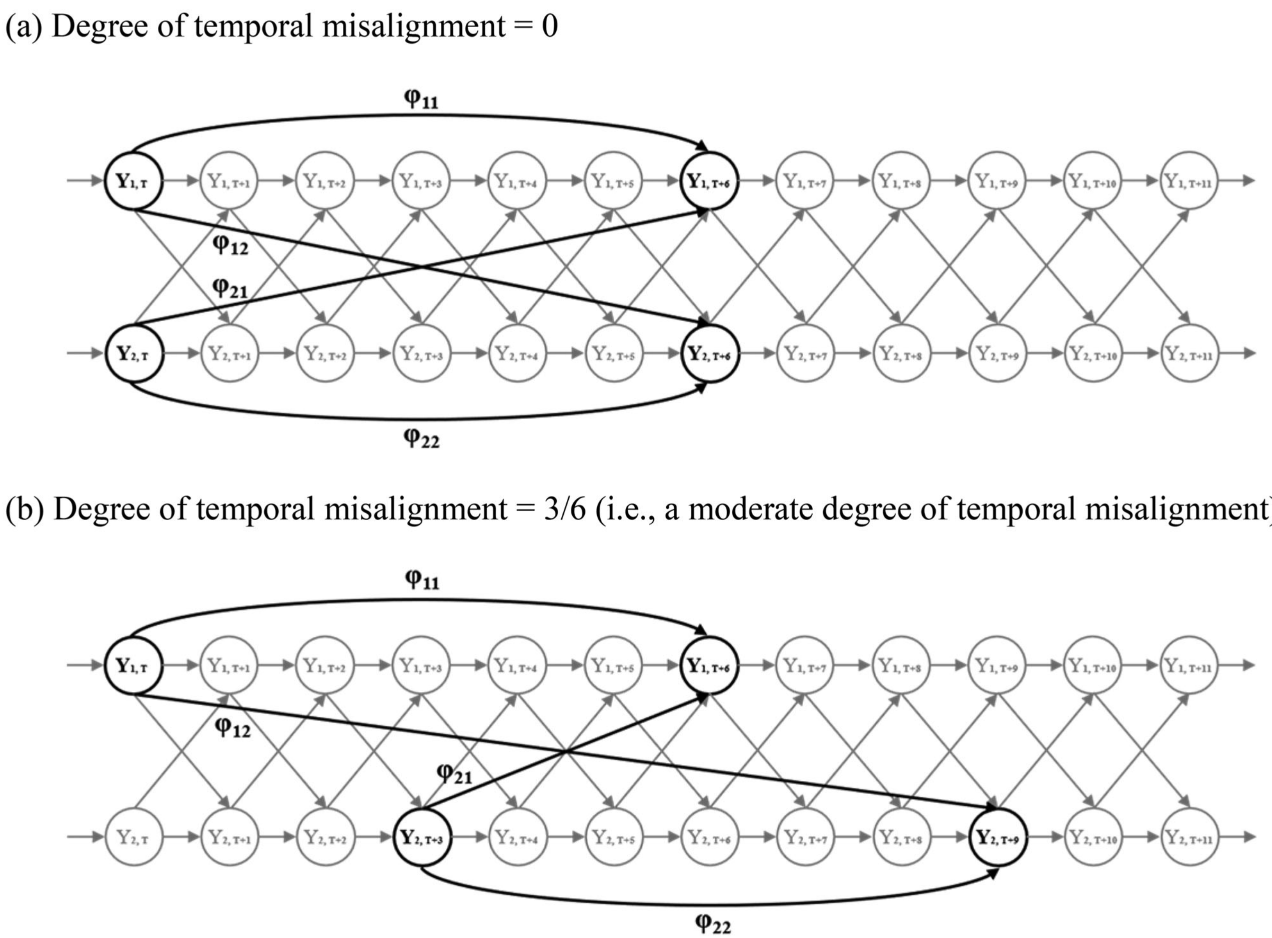

Figure 2. Bidirectional relation between two variables, Y_1 and Y_2, with different degrees of temporal misalignment. φ_{11} and φ_{22} denote autoregressive parameters, and φ_{12} and φ_{21} denote cross-lagged parameters. The gray characters and paths indicate the model of the generated data, and the black bolded characters and paths indicate the model of the adjusted data with different degrees of temporal misalignment.

Table 1. Parameter estimation result of different degrees of temporal misalignment.

Misalignment	φ_{11}	φ_{22}	φ_{12}	φ_{21}
0	0.131	0.130	0.131	0.130
1/6	0.072	0.168	0.058	0.211
2/6	0.058	0.186	0.038	0.292
3/6	0.052	0.194	0.026	0.381
4/6	0.048	0.199	0.019	0.487
5/6	0.047	0.201	0.014	0.617

Notes: φ_{11} and φ_{22} denote the autoregressive effects of Y_1 and Y_2, and φ_{12} and φ_{21} denote the cross-lagged effects between Y_1 and Y_2.

500 parameter estimates for autoregressive and cross-lagged parameters. In addition, we reported the statistical power of autoregressive and cross-lagged parameters by calculating the percentage of significant parameters over the 500 replications.

2.2. Results

2.2.1. Influences of Temporal Misalignment on the Accuracy of Parameter Estimation

Table 1 presents the results of parameter estimation of different degrees of temporal misalignment. The results show that the bias of the estimation results for all four parameters dramatically increases with the degree of temporal misalignment. Specifically, for the autoregressive parameters, the autoregressive effect of Y_1 (i.e., φ_{11}) decreases, while the autoregressive effect of Y_2 (i.e., φ_{22}) increases as the degree of temporal misalignment increases. For the cross-lagged parameters, the cross-lagged effect of Y_1 on Y_2 (i.e., φ_{12}) increase rapidly,

while the cross-lagged effect of Y_2 on Y_1 (i.e., φ_{21}) decrease rapidly as the degree of temporal misalignment increases. In addition, the autoregressive and cross-lagged effects in the baseline condition are very close to 0.131, which validates the formula we mentioned above (i.e., $\Phi^{(n)} = 2^{n-1}a^n$).

2.2.2. Influences of Temporal Misalignment on the Statistical Power of Parameters

For the cross-lagged effect of Y_1 on Y_2 (i.e., φ_{12}), temporal misalignment has a negative impact on its statistical power. As revealed in Figure 3, the cross-lagged effect of Y_1 on Y_2 (i.e., φ_{12}) decreases rapidly as the degree of temporal misalignment increases. Notably, when the two variables are almost moderately misaligned in time (i.e., degree of temporal misalignment = 3), the statistical power of this cross-lagged parameter will be lower than 0.80, which may largely influence the conclusions of empirical studies. In addition, for other parameters (i.e., φ_{11}, φ_{22}, and φ_{21}), their statistical power is greater than or equal to 0.998 for various degrees

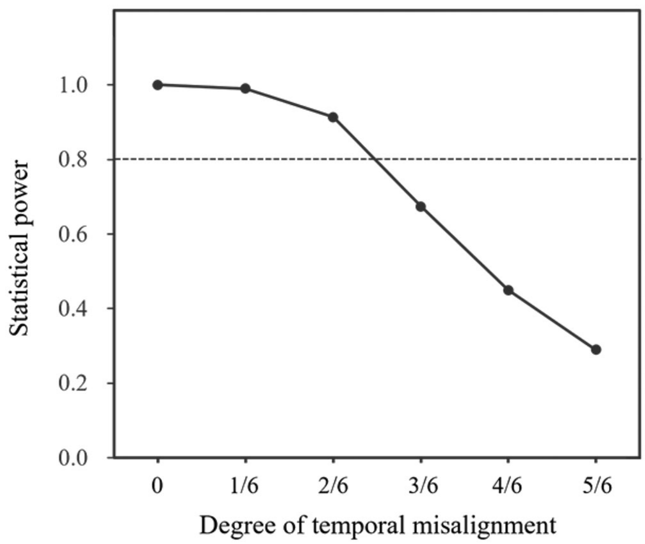

Figure 3. The statistical power of the cross-lagged effect of Y_1 on Y_2 (i.e., φ_{12}) as a function of the degree of temporal misalignment.

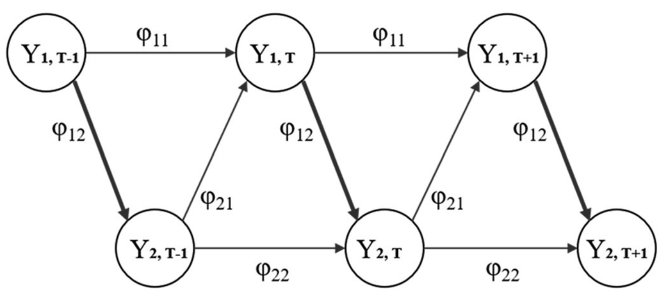

Figure 4. Adjusted model of the bidirectional relation between two temporally misaligned variables, Y_1 and Y_2, with autoregressive parameters φ_{11} and φ_{22}, and cross-lagged parameters φ_{12} and φ_{21}. The adjusted paths are bolded.

of temporal misalignment, indicating that the influence of temporal misalignment on the statistical power of these parameters is relatively small.

3. Study 2: Solutions to Temporal Misalignment

3.1. Two Proposed Solutions

3.1.1. Model Adjustment

One possible solution to the problem of temporal misalignment is to adjust the estimated model. To estimate the autoregressive and cross-lagged effects of two temporally misaligned variables, we establish an adjusted model in Figure 4. In contrast to the naive model in Figure 1, we build paths between two variables measured at the same time (e.g., $Y_{1,\ T\text{-}1} \rightarrow Y_{2,\ T\text{-}1}$, rather than $Y_{1,\ T\text{-}1} \rightarrow Y_{2,\ T}$) to estimate the cross-lagged effect of Y_1 on Y_2. The reason for this is that although Y_1 and Y_2 are measured at the same time, the event represented by Y_1 occurs earlier than the event represented by Y_2 in the same measurement (i.e., the actual time points of the two variables are not aligned). Therefore, the predictive effect of Y_1 on Y_2 in the same measurement can reflect the cross-lagged effect of Y_1 on Y_2. More importantly, in the adjusted model, the time interval corresponding to the effect of Y_1 on Y_2 is much smaller than that in the naive model, and the length of this time interval is closer to that corresponding to the effect of Y_2 on Y_1, which makes the cross-lagged effects between Y_1 and Y_2 more comparable and the inference of causality between Y_1 and Y_2 more reasonable.

3.1.2. Data Interpolation

Another possible solution to the problem of temporal misalignment is to treat temporally misaligned data as data with missing values, so that we can apply the methods for handling missing data to solve the current problem. Researchers proposed a great number of methods to deal with missing values in time series data, including list-wise deletion, data interpolation, multiple imputation, maximum likelihood estimation (Ji et al., 2018; Pratama et al., 2016). Since the data in the current problem are completely misaligned, list-wise deletion is improper, otherwise all data will be deleted. In addition, multiple imputation and maximum likelihood estimation are not appropriate because we have only two variables and no other covariates, and the "missing" values in temporally misaligned data are fundamentally different from the missingness due to subject attrition or response omission in empirical studies.

In contrast, data interpolation may be a more appropriate approach. Data interpolation is a common method used to deal with missingness or unequally spaced intensive longitudinal data in discrete-time dynamic models (Ji et al., 2018). In intensive longitudinal data, discrete observations reflect continuous dynamic processes. For temporally misaligned variables, there are actually unmeasured states of one variable at time points aligned with the other variable, and data interpolation allows interpolation of these unobserved states based on the serial data of the variables themselves. After interpolating the missingness due to temporal misalignment, we are able to describe and analyze the now temporally aligned variables on a denser time scale.

One of the simplest data interpolation methods is to substitute missing values with the mean of adjacent observations (Velicer & Colby, 2005). In addition, spline interpolation is another commonly used method to deal with missing values in intensive longitudinal data (Gasimova et al., 2014; Ribeiro & Piedade, 2022). Therefore, two typical data interpolation methods, mean interpolation and spline interpolation, were used in this study to investigate the effectiveness of the data interpolation method for the problem of temporal misalignment.

3.2. Methods

3.2.1. Procedure

In Study 1, we found that a moderate degree of temporal misalignment in intensive longitudinal data would lead to highly biased estimates of autoregressive and cross-lagged parameters, and low statistical power (i.e., <0.80) of the cross-lagged effect of Y_1 on Y_2. More importantly, the moderate degree of temporal misalignment is common in empirical studies. For the first type of temporal misalignment, for example, there is a moderate degree of misalignment between daytime variables (e.g., negative affect during the day) and nighttime variables (e.g., sleep quality during the night) because a day can be approximated as half day and half night, with negative affect and sleep lasting throughout the day and night, respectively. For the second type of temporal misalignment, for example, there is a moderate degree of misalignment between the accumulative variables (e.g., physical activity, with a time reference of "since you completed the last questionnaire") and the momentary variables (e.g., affect, with a time reference of "at this moment") because the former can be approximated as occurring at the midpoint of the measurement interval. Therefore, a moderate degree of temporal misalignment was used in Study 2 to explore the effectiveness of two proposed solutions to the problem of temporal misalignment.

We first simulated the data of two variables in M*plus* 8.3 (Muthén & Muthén, 2017) based on DSEM. The simulation was replicated for 500 times. Then, adjusted data with a moderate temporal misalignment was created by retaining half of the original observations for both variables. For the model adjustment method, we simply made one adjustment to the estimated model: we estimated the cross-lagged effect of Y_1 on Y_2 by estimating the path value from Y_1 to the contemporaneous Y_2 (e.g., $Y_{1,\ \text{T-1}} \rightarrow Y_{2,\ \text{T-1}}$), rather than from Y_1 to the subsequent Y_2 (e.g., $Y_{1,\ \text{T-1}} \rightarrow Y_{2,\ \text{T}}$). For the data interpolation method, we first interpolated temporally misaligned variables with two typical interpolation methods: (a) mean interpolation and (b) spline interpolation using the R function *na.spline* in the *zoo* package (Zeileis & Grothendieck, 2005). Then, the interpolated data was fitted directly to DSEM without considering temporal misalignment (i.e., naïve estimation). The R package *MplusAutomation* (Hallquist & Wiley, 2018) was used to replicate the model estimation for 500 times. M*plus* syntax for the naïve estimation and the model adjustment method can be found in Appendix B. Note that the model settings for the naive estimation method and the data interpolation method are the same (their input data are different), so we do not present the M*plus* syntax for the data interpolation method separately.

3.2.2. Simulation Conditions

Table 2 presented eight conditions we considered in this simulation study. We first set a reference condition where sample size (N) was equal to 200, the number of time points per subject (T) was equal to 50, the autoregressive and cross-lagged effects were all equal to 0.3. Then, we varied the sample size, the number of time points per subject, parameter values, and the continuity of timescale to test the effectiveness of proposed solutions. Other parameters for generating data based on DSEM are set as follows. At the within level, the variances of Y_1 and Y_2 were fixed as 0.6, and the correlation between residuals of Y_1 and Y_2 was fixed as 0.4. At the between level, the variances of Y_1 and Y_2 were fixed as 1, and the correlation between Y_1 and Y_2 was fixed as 0.5. Note that for these parameters of less interest in applied studies, we set different values in Study 2 than in Study 1 to present the impacts of temporal misalignment in more cases.

Table 2. Simulation conditions.

Condition		N	T	a_{11}	a_{22}	a_{12}	a_{21}
Reference condition	1	**200**	**50**	**0.3**	**0.3**	**0.3**	**0.3**
Test N	2	**100**	50	0.3	0.3	0.3	0.3
	3	**300**	50	0.3	0.3	0.3	0.3
Test T	4	200	**30**	0.3	0.3	0.3	0.3
	5	200	**100**	0.3	0.3	0.3	0.3
Test parameter values	6	200	50	**0.4**	**0.2**	**0.2**	**0.4**
	7	200	50	**0.2**	**0.4**	**0.4**	**0.2**
Test discontinuous timescale	8	200	**50**[a]	0.3	0.3	0.3	0.3

Notes: N denotes sample size; T denotes the number of time points per subject; Bold values indicate the parameters varied in each simulation condition. [a]With discontinuous timescale.

For sample size, we used 100, 200, and 300 to represent the small, medium and large samples in empirical studies that collect intensive longitudinal data. For the number of time points per subject, we used 30, 50, and 100 to represent time points in some typical designs in which intensive longitudinal data are collected. For example, in a two-week daily diary study, if one measurement is administered in the morning and one in the evening, there will be 28 measurements per subject in total. Therefore, we set the number of time points per subject to 30 to reflect this typical design. As another example, in a typical ten-day study using the experience sampling method, if there are five measurements per day, each subject will have a total of 50 observations. However, we need to double the number of actual observations to calculate the number of time points per subject in the simulation (i.e., $T = 50 \times 2 = 100$) because we need to remove half of the observations in the generated data to simulate the observed data with a moderate degree of temporal misalignment.

For the parameter values, we set conditions 6 and 7 to reflect a question of interest in empirical studies: who has a greater effect between two variables on each other? Specifically, we set the autoregressive effect of one variable and the cross-lagged effect on that variable as large effects (i.e., 0.4), and the autoregressive effect of and the cross-lagged effect on the other variable as small effects (i.e., 0.2). It is worth clarifying that condition 6 and 7 are not equivalent, as Study 1 has showed that the impacts of temporal misalignment on all four parameter estimates were different.

Finally, we set condition 8 to simulate a typical situation when using empirical sampling methods and/or ecological momentary assessments. Considering that in these types of designs, data at certain time points are not measurable (e.g., during nighttime sleep), it is necessary to explore the performance of the two proposed solutions in data with discontinuous time scales.

3.2.3. Evaluations

To evaluate the performance of the two proposed solutions, we first calculated the mean ($\overline{\varphi}$) of 500 parameter estimates for autoregressive and cross-lagged parameters. To compare the parameter estimation results of the naïve estimation with those of the model adjustment method and the data interpolation method, we calculated the relative bias $(\overline{\varphi} - \Phi)/\Phi$, where Φ is the expected values of four parameters. Note that the expected values of four parameters varied in different methods. In the data interpolation method, the expected values of all parameters are equal to the corresponding simulated parameters; however, in the other two methods, the expected values of four parameters should be calculated as follows.

In the naive estimation method, researchers would blindly treat the temporally misaligned data as aligned and expect to obtain the parameter values at corresponding time intervals. In conditions 1 through 5 and condition 8, all four parameters (i.e., a) are set to 0.3 to generate data, so the expected values of the parameters should satisfy the equations introduced in Study 1 (i.e., $\Phi^{(n)} = 2^{n-1}a^n$) and equal to 0.18 as the number of degrees of temporal misalignment (i.e., n) is equal to 2 in study 2. In conditions 6 and 7, the parameters in the generated data are not all equal. In these conditions, the expected values of the autoregressive and cross-lagged parameters for Y_1 and Y_2 can be calculated by the following equations (see Online Supplementary Material A for the derivation):

$$\Phi_{11}^{(n)} = \Phi_{21}^{(n)} = a_1(a_1 + a_2)^{n-1} \quad (2a)$$

$$\Phi_{12}^{(n)} = \Phi_{22}^{(n)} = a_2(a_1 + a_2)^{n-1} \quad (2b)$$

where n is the number of degrees of temporal misalignment and is set to 2 in Study 2, and a_1 and a_2 are the simulated values of the autoregressive and cross-lagged parameters for Y_1 and Y_2, respectively.

In the model adjustment method, the expected values of four parameters can be calculated using the following formula (See Online Supplementary Material B for the derivation):

$$\Phi_{11} = a_{11}^2 \quad (3a)$$

$$\Phi_{22} = a_{22}^2 \quad (3b)$$

$$\Phi_{12} = a_{12} \quad (3c)$$

$$\Phi_{22} = a_{21} \quad (3d)$$

where Φ_{11} and Φ_{22} are the expected values of the autoregressive parameters for Y_1 and Y_2, and Φ_{12} and Φ_{21} are the expected values of the cross-lagged parameters between Y_1 and Y_2. a_{11} and a_{22} are the simulated values of the autoregressive parameters for Y_1 and Y_2, and a_{12} and a_{21} are the simulated values of cross-lagged parameters between Y_1 and Y_2.

In addition, we calculated the standard error (*SE*) of estimation as the standard deviation of the 500 parameter estimates. Moreover, the statistical power of autoregressive and cross-lagged parameters was calculated as the percentage of significant cases over the 500 replications.

3.3. Results

3.3.1. Comparison of Naïve Estimation with Model Adjustment and Data Interpolation

Table 3 presented parameter estimation results using the naïve estimation, the model adjustment method and the data interpolation method in the reference condition. Similar to the result in Study 1, the naïve estimation led to biased results of parameter estimates, especially for the cross-lagged effect of Y_1 on Y_2 (i.e., φ_{12}), which was highly underestimated. This made sense because the time interval corresponding to this effect is the largest in the temporally misaligned data, which led to a weak association between the two observations, and thus, small cross-lagged effect of Y_1 on Y_2.

Table 3. Parameter estimation results in condition 1 (reference condition).

	Solution	Φ	$\bar{\varphi}$	$(\bar{\varphi}-\Phi)/\Phi$	*SE*	Power
$Y_1 \rightarrow Y_1$	Naïve estimation	0.18	0.099	−0.450	0.015	1.000
	Model adjustment	0.09	0.098	**0.089**	0.015	1.000
	Data interpolation	0.3	0.738	1.460	0.008	1.000
$Y_2 \rightarrow Y_2$	Naïve estimation	0.18	0.185	**0.028**	0.015	1.000
	Model adjustment	0.09	0.098	**0.089**	0.015	1.000
	Data interpolation	0.3	0.737	1.457	0.008	1.000
$Y_1 \rightarrow Y_2$	Naïve estimation	0.18	0.059	−0.672	0.014	0.980
	Model adjustment	0.3	0.309	**0.030**	0.015	1.000
	Data interpolation	0.3	0.096	−0.680	0.009	1.000
$Y_2 \rightarrow Y_1$	Naïve estimation	0.18	0.310	0.722	0.015	1.000
	Model adjustment	0.3	0.309	**0.030**	0.015	1.000
	Data interpolation	0.3	0.095	−0.683	0.009	1.000

Notes: Φ denotes the expected value of parameters. $\bar{\varphi}$ denotes the mean of 500 parameter estimates. *SE* denotes the standard error of parameter estimation. Bold values indicate that the absolute value of the relative bias is less than 0.100 (i.e., small relative bias).

Regarding the proposed solution to the problem of temporal misalignment, the model adjustment method performed better. As shown in Table 3, this method yielded the most accurate parameter estimates, with small relative deviations (i.e., less than 0.050) for all four parameters. In contrast, the data interpolation method was not as effective as we expected; in fact, it may be problematic. The autoregressive parameters were largely overestimated, and the cross-lagged effects were underestimated. We will discuss this later in this paper. Additionally, it should be noted that we only present the results obtained with mean interpolation because the results of the two interpolation methods (i.e., mean interpolation and spline interpolation) were similar. Interested readers can find the complete results using two data interpolation methods in Online Supplementary Material C.

3.3.2. The Effectiveness of the Model Adjustment Method

To further examine the effectiveness of the model adjustment method under other conditions, we varied the sample size and the number of time points per subject (Table 4), parameter values (Table 5), and the continuity of timescale (Table 6), and compared the results of the model adjustment method with the naive estimation. For the data interpolation method, we do not present and elaborate the results here because the results of this method in the above-conditions (i.e., conditions 2–8) showed a similar pattern to those in the reference condition.

As shown in Table 4, the sample size and the number of time points per subject do not affect the accuracy of the parameter estimates of the model adjustment method. The relative bias of the four parameter estimates is consistently small (i.e., <0.050) when the sample size varies from 100 to 300 and the number of time points varies from 30 to 100, even though the standard error increases and the statistical

Table 4. Parameter estimation of conditions testing sample size and the number of time points per subject.

	Naïve estimation					Model adjustment				
	Φ	$\bar{\varphi}$	$\frac{\bar{\varphi}-\Phi}{\Phi}$	*SE*	Power	Φ	$\bar{\varphi}$	$\frac{\bar{\varphi}-\Phi}{\Phi}$	*SE*	Power
Condition 2 ($N=100$, $T=50$)										
$Y_1 \rightarrow Y_1$	0.18	0.098	−0.456	0.022	0.994	0.09	0.097	0.078	0.020	0.994
$Y_2 \rightarrow Y_2$	0.18	0.186	0.033	0.023	1.000	0.09	0.095	0.056	0.020	0.994
$Y_1 \rightarrow Y_2$	0.18	0.057	−0.683	0.020	0.740	0.3	0.310	0.033	0.021	1.000
$Y_2 \rightarrow Y_1$	0.18	0.309	0.717	0.022	1.000	0.3	0.308	0.027	0.022	1.000
Condition 3 ($N=300$, $T=50$)										
$Y_1 \rightarrow Y_1$	0.18	0.099	−0.450	0.013	1.000	0.09	0.097	0.078	0.013	1.000
$Y_2 \rightarrow Y_2$	0.18	0.185	0.028	0.013	1.000	0.09	0.096	0.067	0.012	1.000
$Y_1 \rightarrow Y_2$	0.18	0.058	−0.678	0.012	0.998	0.3	0.309	0.030	0.012	1.000
$Y_2 \rightarrow Y_1$	0.18	0.310	0.722	0.012	1.000	0.3	0.310	0.033	0.012	1.000
Condition 4 ($N=200$, $T=30$)										
$Y_1 \rightarrow Y_1$	0.18	0.101	−0.439	0.021	0.998	0.09	0.098	0.089	0.021	0.998
$Y_2 \rightarrow Y_2$	0.18	0.186	0.033	0.022	1.000	0.09	0.097	0.078	0.020	0.998
$Y_1 \rightarrow Y_2$	0.18	0.059	−0.672	0.020	0.836	0.3	0.309	0.030	0.020	1.000
$Y_2 \rightarrow Y_1$	0.18	0.310	0.722	0.020	1.000	0.3	0.308	0.027	0.019	1.000
Condition 5 ($N=200$, $T=100$)										
$Y_1 \rightarrow Y_1$	0.18	0.099	−0.450	0.010	1.000	0.09	0.098	0.089	0.010	1.000
$Y_2 \rightarrow Y_2$	0.18	0.186	0.033	0.012	1.000	0.09	0.098	0.089	0.011	1.000
$Y_1 \rightarrow Y_2$	0.18	0.058	−0.678	0.011	1.000	0.3	0.311	0.037	0.011	1.000
$Y_2 \rightarrow Y_1$	0.18	0.311	0.728	0.011	1.000	0.3	0.311	0.037	0.011	1.000

Notes: Φ denotes the expected value of parameters. $\bar{\varphi}$ denotes the mean of 500 parameter estimates. *SE* denotes the standard error of parameter estimation.

Table 5. Parameter estimation of conditions testing parameter values.

	Naïve estimation					Model adjustment				
	Φ	$\bar{\varphi}$	$\frac{\bar{\varphi}-\Phi}{\Phi}$	*SE*	Power	Φ	$\bar{\varphi}$	$\frac{\bar{\varphi}-\Phi}{\Phi}$	*SE*	Power
Condition 6 ($N=200$, $T=50$)										
$Y_1 \rightarrow Y_1$	0.24	0.167	−0.304	0.016	1.000	0.16	0.165	0.031	0.016	1.000
$Y_2 \rightarrow Y_2$	0.12	0.127	−0.058	0.015	1.000	0.04	0.047	0.175	0.016	0.800
$Y_1 \rightarrow Y_2$	0.12	0.058	−0.517	0.015	0.974	0.2	0.234	0.170	0.016	1.000
$Y_2 \rightarrow Y_1$	0.24	0.356	−0.483	0.013	1.000	0.4	0.356	−0.110	0.013	1.000
Condition 7 ($N=200$, $T=50$)										
$Y_1 \rightarrow Y_1$	0.12	0.048	−0.600	0.016	0.830	0.04	0.046	0.150	0.016	0.796
$Y_2 \rightarrow Y_2$	0.24	0.236	−0.017	0.016	1.000	0.16	0.164	0.025	0.014	1.000
$Y_1 \rightarrow Y_2$	0.24	0.048	−0.800	0.015	0.892	0.4	0.357	−0.108	0.014	1.000
$Y_2 \rightarrow Y_1$	0.12	0.234	0.950	0.015	1.000	0.2	0.233	0.165	0.015	1.000

Notes: Φ denotes the expected value of parameters. $\bar{\varphi}$ denotes the mean of 500 parameter estimates. *SE* denotes the standard error of parameter estimation.

Table 6. Parameter estimation of conditions testing discontinuous timescale.

	Naïve estimation					Model adjustment				
	Φ	$\bar{\varphi}$	$\frac{\bar{\varphi}-\Phi}{\Phi}$	*SE*	Power	Φ	$\bar{\varphi}$	$\frac{\bar{\varphi}-\Phi}{\Phi}$	*SE*	Power
Condition 8 ($N=200$, $T=50$[a])										
$Y_1 \rightarrow Y_1$	0.18	0.098	−0.456	0.016	1.000	0.09	0.096	0.067	0.016	1.000
$Y_2 \rightarrow Y_2$	0.18	0.186	−0.033	0.017	1.000	0.09	0.099	0.100	0.016	1.000
$Y_1 \rightarrow Y_2$	0.18	0.059	−0.672	0.016	0.942	0.3	0.309	0.030	0.014	1.000
$Y_2 \rightarrow Y_1$	0.18	0.311	0.728	0.016	1.000	0.3	0.311	0.037	0.016	1.000

Notes: Φ denotes the expected value of parameters. $\bar{\varphi}$ denotes the mean of 500 parameter estimates. *SE* denotes the standard error of parameter estimation. [a]With discontinuous timescale.

power of the autoregressive parameters decrease slightly when the sample size or the number of time points decreases. More importantly, the model adjustment method always performed better in terms of parameter estimation and statistical power estimation compared to the naive estimation.

Table 5 presents the parameter estimation results when the simulated parameter values are varied. Under these conditions, the relative bias of the cross-lagged effects estimated using the model adjustment method is relatively larger than that in the reference condition; however, the model adjustment method still shows higher accuracy of the parameter estimation compared with the naïve estimation method. In addition, the statistical power of the cross-lagged effects in the model adjustment method is higher than that of the naïve estimation method. Therefore, the model adjustment method can be used to better estimate and compare the reciprocal effects between temporally misaligned variables.

In addition, the model adjustment method was also found to be effective in data with discontinuous timescale. As shown in Table 6, compared to the results of naive estimation, the relative bias of the parameters is smaller (i.e., <0.050) and the statistical power is higher when the model adjustment method is applied. Therefore, the effectiveness of the model adjustment method is not affected by the continuity of timescale, which indicates that the model adjustment method can be used to address the problem of temporal misalignment for both data with continuous timescale (e.g., daily diary data) and discontinuous timescale (e.g., some data collected by experience sampling method).

4. Study 3: Empirical Application on Daily Diary Data

4.1. Empirical Data

We first present an example using daily diary data with temporally misaligned variables to show the differences of the parameter estimation results of different methods (i.e., naïve estimation, model adjustment, and data interpolation). This example investigated the bidirectional relation between negative affect during the day and mood on final wakening. Forty-seven undergraduates participated in a two-week study, during which they reported their negative affect before sleep every day and assessed their mood upon awakening the next morning. Negative affect was measured by five items from the Positive and Negative Affect Scale (PANAS; Kercher, 1992). Participants were asked to assess the extent to which they had the following feelings: upset, afraid, nervous, scared, and distressed on that day, from 1 ("very slight or not at all") to 5 ("extremely"). The total score of the five items was used to represent individuals' negative affect during the day. Mood on final wakening was measured by one item, which asked participants to rate their mood on their final awakening, from 1 ("very tense") to ("very calm"). We tested the bidirectional relation between these two variables by fitting them into DSEM in M*plus* 8.3 (Muthén & Muthén, 2017) using the naive estimation, the model adjustment method, and the data interpolation method (i.e., mean interpolation).

4.2. Results

Table 7 shows the parameter estimation results using the naïve estimation and the two solutions proposed in this study. The results of the naïve estimation showed significant autoregressive effects of negative affect during the day and mood on final awakening. More importantly, there was a

Table 7. Parameter estimates of the bidirectional relation between negative affect during the day and mood on final wakening obtained by different estimation methods.

	Naïve estimation			Model adjustment			Data interpolation		
	β	*SE*	95%CI	*β*	*SE*	95%CI	*β*	*SE*	95%CI
φ_{NN}	**0.267**	0.054	[0.157, 0.368]	**0.266**	0.057	[0.146, 0.376]	**0.732**	0.024	[0.685, 0.778]
φ_{MM}	**0.115**	0.051	[0.012, 0.214]	**0.102**	0.052	[0.002, 0.206]	**0.753**	0.024	[0.703, 0.799]
φ_{NM}	0.051	0.054	[−0.059, 0.153]	**−0.124**	0.055	[−0.230, −0.011]	**−0.078**	0.021	[−0.119, −0.037]
φ_{MN}	**−0.136**	0.043	[−0.218, −0.055]	**−0.134**	0.044	[−0.222, −0.049]	−0.001	0.025	[−0.049, 0.047]

Notes: φ_{NN} and φ_{MM} denote the autoregressive parameters of negative affect during the day and mood on final wakening. φ_{NM} and φ_{MN} denote the cross-lagged parameters between negative affect during the day and mood on final wakening. Bold values indicate significant effects.

significant cross-lagged effect of mood on final awakening on negative affect during the day, suggesting that if participants felt calmer on final awakening, they would have less negative affect during the day. In contrast, the cross-lagged effect of negative affect during the day on mood on final awakening was not significant; however, this was not the same in the results of the model adjustment method. In fact, after adjusting the estimation model, participants' negative affect during the day could negatively predict their mood when they finally woke up the next morning.

Considering that negative affect during the day and mood on final awakening were not aligned in time, the cross-lagged effect of negative affect during the day on mood on final awakening was actually the predicting effect of negative affect during one day on the next measures of the mood on final awakening next day morning (i.e., mood on the third day), which corresponded to a much larger time interval compared to the cross-lagged effect in the other direction. Thus, it made sense that this cross-lagged effect was smaller, and was less likely to be significant in the naïve estimation. In the model adjustment method, however, the cross-lagged effect of negative affect during the day on mood on final awakening was the predicting effect of negative affect during the day on mood on final awakening on the second day, not the third day. Since the time interval between these two variables was smaller and more comparable to the time interval in the other direction, the corresponding result (i.e., the cross-lagged effects between these two variables were significant in both directions) were more reasonable.

In addition, the results of the data interpolation method were largely different from those of the naïve estimation and the model adjustment method. First, in the results of the data interpolation method, the autoregressive effects of negative affect during the day and mood on final awakening were much larger than those estimated by the other two methods, and these extremely large effects were unusual, and thus may be unreasonable to be found in empirical studies. Moreover, the cross-lagged effects between negative affect during the day and mood on final awakening were relatively small or even insignificant, which also differed from the results of the other two methods. Thus, the parameter estimation results of the data interpolation method showed a similar pattern to that of the simulation study (i.e., overestimate the autoregressive effects and underestimate the cross-lagged effects), suggesting that the data interpolation method may be an inappropriate solution to the problem of temporal misalignment.

5. Study 4: Empirical Application on Experience Sampling Data

5.1. Empirical Data

Another example is a diet study that used the experience sampling method and collected temporally misaligned data. This study explored the bidirectional relation between unhealthy snacking and hunger. A total of fifty-nine undergraduates participated in this one-week study, during which they need to finish an online questionnaire five times per day at 11 a.m., 2 p.m., 5 p.m., 8 p.m. and 11 p.m. To measure unhealthy snacking behavior, we summarized six categories of unhealthy snacks, such as sugar-sweetened beverages, based on food codes adapted to the APS (Kelly et al., 2016), and provided participants with detailed information and examples. In each questionnaire, participants were first asked to report whether they had eaten any snacks since they completed the previous questionnaire. If they had eaten any of the snacks, they were then required to report the number of times they had eaten each type of unhealthy snack, from one to nine times. The total number of times the six categories of unhealthy snacks were consumed was calculated to represent individual's unhealthy snacking behavior. In addition, participants were also asked to rate their hunger from 1 ("at this moment, not hungry at all") to 9 ("at this moment, extremely hungry") in each questionnaire. The bidirectional relation between unhealthy snacking and hunger feeling was tested in DSEM in M*plus* 8.3 (Muthén & Muthén, 2017) by using the naive estimation, the model adjustment method, and the data interpolation method (i.e., mean interpolation).

5.2. Results

Table 8 shows the parameter estimation results of the bidirectional relation between unhealthy snacking and hunger using different methods. In the results of naïve estimation, only the autoregressive effect of hunger was significant, while other autoregressive and cross-lagged effects were not significant. However, a significant cross-lagged effect of unhealthy snacking on hunger was found in the results of the model adjustment method, which suggested that unhealthy snacking alleviated subsequent hunger. The difference in this cross-lagged effect can probably be attributed to the smaller time interval between unhealthy snacking and hunger in the adjusted model. In the naïve estimation, the cross-lagged effect of unhealthy snacking on hunger was the predictive effect of unhealthy snack intake between the last

Table 8. Parameter estimates of the bidirectional relation between unhealthy snacking and hunger obtained by different estimation methods.

	Naïve estimation			Model adjustment			Data interpolation		
	β	SE	95%CI	β	SE	95%CI	β	SE	95%CI
φ_{UU}	0.014	0.026	[−0.042, 0.062]	0.016	0.027	[−0.039, 0.065]	**0.646**	0.015	[0.616, 0.676]
φ_{HH}	**−0.128**	0.027	[−0.179, −0.074]	**−0.133**	0.027	[−0.185, −0.079]	**0.589**	0.014	[0.561, 0.615]
φ_{UH}	0.009	0.046	[−0.081, 0.096]	**−0.069**	0.032	[−0.128, −0.007]	**−0.035**	0.017	[−0.070, −0.003]
φ_{HU}	0.010	0.033	[−0.053, 0.080]	0.010	0.031	[−0.045, 0.079]	**0.037**	0.013	[0.011, 0.063]

Notes: φ_{UU} and φ_{HH} denote the autoregressive parameters of unhealthy snacking and hunger. φ_{UH} and φ_{HU} denote the cross-lagged parameters between unhealthy snacking and hunger. Bold values indicate significant effects.

measurement and the current measurement on hunger at the next measurement, whereas in the model adjustment method, this effect was the predictive effect of unhealthy snack intake between the last measurement and the current measurement on hunger at that measurement, not next measurement. Thus, the model adjustment method revealed a significant effect of unhealthy snack intake on subsequent hunger.

In addition, the data interpolation method showed a similar pattern of results to the previous example. For example, the autoregressive effects of unhealthy snacking and hunger were much larger than those found in the other two methods. This again suggested that interpolation of temporally misaligned data may not be as effective as we intuitively expected.

6. Discussion

The reciprocal effect or causality between variables is one of the main interests of social scientists (Hecht & Zitzmann, 2021; Usami et al., 2019). From a dynamic perspective, researchers collect intensive longitudinal data and estimate the autoregressive and cross-lagged effects of two variables to investigate how changes in one variable are influenced by previous values of that variable and the other variable. Based on this, causal inference between variables can be made by comparing the magnitude of their cross-lagged effects. However, this may be problematic when two variables are not aligned in time.

In this study, we performed a preliminary exploration of the temporal misalignment problem in intensive longitudinal data based on DSEM. We first found that the results of parameter estimation were significantly affected as the degree of temporal misalignment increased. More importantly, in the two proposed solutions, the model adjustment method was shown to be effective under various simulation conditions. Finally, we demonstrated the different results using three different methods (i.e., naive estimation, model adjustment, and data interpolation) in temporally misaligned data of two empirical studies.

6.1. Consequences of Temporal Misalignment

As we expected, the bias in the estimates of the autoregressive and cross-lagged effects of two temporally misaligned variables grows as the degree of temporal misalignment increases. Even worse, the cross-lagged effect corresponding to the larger time interval decreases rapidly, with the statistical power of this effect falling below 0.80 (i.e., the lowest value of generally accepted statistical power) when a moderate degree of temporal misalignment is reached. This suggests that a moderate degree of temporal misalignment may significantly alter the findings and conclusions of empirical studies, and therefore it is inappropriate to blindly treat temporally misaligned variables as aligned to estimate their cross-lagged effects and infer their causal effects.

6.2. Solutions to Temporal Misalignment

To address the problem of temporal misalignment, we proposed two possible solutions (i.e., the model adjustment method and the data interpolation methods) and examined the effectiveness of these two solutions by comparing their parameter estimation results with those of the naive estimation. The model adjustment method proved to be a practical solution under a variety of conditions with different settings (e.g., different sample sizes and number of time points per subject). This method replaces the cross-lagged effect corresponding to a larger time interval in the naive estimation with the correlation between two variables in the same observation that have a smaller time interval. Using this approach, the difference in the time intervals corresponding to two cross-lagged effects between temporal misaligned variables becomes smaller, so that the two cross-lagged effects are more comparable. Therefore, it is more convincing to infer reciprocal or causal relations between variables.

However, it should be noted that the model adjustment method cannot estimate contemporaneous relations between variables. The contemporaneous relation is meaningful for intensive longitudinal data collected through empirical sampling method or ecological momentary assessment. It reflects the extent to which two variables co-occur after accounting for the effects of the previous time point, suggesting a potential causal relation between variables that occurs faster than the specific time interval used in a study (Epskamp et al., 2018). However, because the model estimation method only adjusts the estimated model without changing the temporally misaligned data itself, there are no concurrent variables in the data to estimate contemporaneous relations between variables. Furthermore, one should note that the association between the residuals of two temporally misaligned variables (e.g., unhealthy snacking and hunger) estimated by the naïve model does not reflect their simultaneous association or co-occurrence. In fact, it would be more appropriate to interpret this association as a cross-lagged effect of an earlier-occurring variable (e.g., unhealthy snacking) on a subsequent variable (e.g., hunger). If researchers are truly interested in the contemporaneous relation between variables, they may need to adjust the measure to match the time blocks of the two variables, for example, by asking participants to report their average feelings (e.g., hunger) and performance (e.g., unhealthy snacking behavior) after completing the previous questionnaire. In this case, the simultaneous association between variables could represent their contemporaneous relation (e.g., whenever the person ate an unhealthy snack, he or she felt more/less hungry). In addition, for some temporally misaligned data collected by daily diaries, the contemporaneous relation between the variables may not be reasonable because there is no overlap between the time blocks of the two variables (e.g., negative affect during the day and mood on final waking). Therefore, it is appropriate to use the model adjusted method to estimate cross-lagged effects between temporally misaligned daily diary data.

The other proposed solution to the problem of temporal misalignment is data interpolation; however, it was found to be ineffective in this study. Although only two typical interpolation methods for longitudinal data were used in this study (i.e., mean interpolation and spline interpolation), the parameter estimation results of both methods showed a similar biased pattern of bias: overestimation of autoregressive effects while underestimation of cross-lagged effects. This may be attributed to the fact that both methods interpolate the "missing" values only based on the information of that variable without considering the influence of the other variable. As a result, both mean interpolation and spline interpolation produced large bias in the parameter estimates. However, we believed that the idea of data interpolation is still valuable. First, temporally misaligned variables in intensive longitudinal data can be regarded as a special form of missing data. Although the interpolation method based only on the information of the variables themselves (such as the mean interpolation and spline interpolation used in this study) introduced bias in parameter estimation in this study, it has the potential to be an effective solution to the problem of temporal misalignment if the information of both variables can be considered in the interpolation. Furthermore, if a more accurate parameter estimation result can be obtained by using a suitable interpolation method, the data interpolation method can answer questions that the model adjustment method cannot. For example, since the data interpolation method can interpolate temporally misaligned data to aligned data, it is possible to investigate the contemporaneous relation between variables based on their simultaneous association. Therefore, although the interpolation methods used in this study are shown to be inappropriate, the idea of data interpolation still has great research prospects.

6.3. Limitations and Future Directions

This study has several limitations. First, although we found the model adjustment method to be a practical solution to the problem of temporal misalignment, it should be noted that we tested its effectiveness primarily based on a moderate degree of temporal misalignment, as Study 1 suggested that the parameters estimates and statistical power changed substantially when the two variables are moderately misaligned. In addition, this method does not allow estimating contemporaneous relations between variables, although such relations are meaningful between variables that may occur simultaneously. Nevertheless, we recommend that future researchers fit temporally misaligned data to the adjusted model because its parameter estimation results are more accurate than those of the naive estimation, especially in the estimation of cross-lagged effects. Considering that examining the reciprocal effects between variables is always one of the core objectives of research (Usami et al., 2019), adjusting the model makes the cross-lagged effects between variables more comparable, which is essential to obtain valid empirical conclusions. But still, more research on coping strategies for this problem is strongly recommended in the future.

For the data interpolation method, only two typical interpolation methods (i.e., mean interpolation and spline interpolation) were used to test its performance. While there are a large number of other interpolation methods that have not been tested, we believe that they may also produce similar results to the methods that we used, since most of these methods are essentially the same: they only interpolate data based on information of the current variable, without considering the influence of other variables. Considering that temporally misaligned data can be regarded as a special type of missing data, and data interpolation is a common strategy for dealing with missingness, the idea of data interpolation may be feasible, and it may be more helpful to interpolate "missing" values of temporally misaligned data by considering the interplay of two variables. However, how such interpolation can be accomplished and whether such data interpolation methods can more effectively address the problem of temporal misalignment remain to be investigated in the future.

In addition, we only examined the effectiveness of the two proposed solutions in several conditions by varying the sample size, the number of time points per subject, the parameter values and the continuity of the time scale. However, it is not clear whether other factors have an impact on the performance of proposed solutions. For example, missingness is a common phenomenon in intensive longitudinal data, and missingness in temporally misaligned data may affect the parameter estimation results of different solutions. Since temporally misaligned data can be considered as "missing" 50% of the data, considering the impact of other causes of missingness would further increases the complexity of the data and the difficulty of model estimation, making it more challenging to clarify the problem of temporal misalignment. Therefore, as a preliminary investigation of temporal misalignment, this study does not further explore the impact of missingness. Nevertheless, future studies may still need to consider other factors (including missingness) that affect the performance of proposed solutions to draw more solid conclusions.

Finally, this study explored possible solutions to the problem of temporal misalignment based only on DSEM, a commonly used modeling approach in the discrete-time modeling framework. However, one may wonder whether this problem can be more easily solved by continuous-time modeling approaches. To the best of our knowledge, the answer is probably no. Previous studies have confirmed the effectiveness of continuous-time modeling methods in dealing with the time interval dependence problem (de Haan-Rietdijk et al., 2017). For example, ctsem (Driver et al., 2017), a useful R package for continuous-time structural equation modeling, allows different time intervals between observations and each person can have his/her own specific series of observations, which effectively solves the problem of unequal time intervals. However, this modeling approach does not allow different time scales between different variables, so it cannot reflect the temporal misalignment of variables, but can only treats temporally misaligned data as aligned. Therefore, the problem of temporal misalignment in intensive longitudinal data cannot be avoided or easily solved in the continuous-time modeling framework. Although there is no existing continuous-time modeling approach that can be directly used to solve the problem of temporal misalignment, we believe that it is intriguing but also challenging to find possible solutions based on the continuous-time modeling framework, and this may be an important path for future research.

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Appendix A. M*plus* syntax for data simulation

```
TITLE: Study 1-Data simulation
MONTECARLO:
   NAMES ARE Y1 Y2;
   NOBS = 60000;
   NREP = 500;
   NCSIZES = 1;
   CSIZES = 200(300);
   LAGGED = Y1(1) Y2(1);
   REPSAVE = ALL;
   SAVE = Study1_rep*.dat;
ANALYSIS:
   TYPE = TWOLEVEL RANDOM;
   ESTIMATOR = BAYES;
   PROCESSORS = 2;
   BITER = (1000);
MODEL POPULATION:
   %WITHIN%
   Y1 on Y1&1 @0.4;
   Y2 on Y2&1 @0.4;
   Y1 on Y2&1 @0.4;
   Y2 on Y1&1 @0.4;
   Y1 @0.7;
   Y2 @0.7;
   Y1 with Y2 @0.1;
   %BETWEEN%
   Y1 @1;
   Y2 @1;
   Y1 with Y2 @0.4;
MODEL:
   %WITHIN%
   Y1 on Y1&1;
   Y2 on Y2&1;
   Y1 on Y2&1;
   Y2 on Y1&1;
   %BETWEEN%
   Y1 with Y2;
```

Appendix B. M*plus* syntax for the Naïve estimation and the model adjustment method

```
TITLE: This is an example for the naïve estimation of a DSEM
DATA: FILE IS temporally misaligned data.csv;
VARIABLE:
   NAMES = ID TIMESTAMP Y1 Y2;
   USEVAR = Y1 Y2;
   MISSING ARE ALL(999);
   CLUSTER = ID;
```

```
    LAGGED = Y1(1) Y2(1);
    TINTERVAL = TIMESTAMP(1);
ANALYSIS:
    TYPE = TWOLEVEL RANDOM;
    ESTIMATOR = BAYES;
    PROCESSORS = 2;
    BITER = (1000);
    THIN = 10;
MODEL:
    %WITHIN%
    Y1 on Y1&1;
    Y2 on Y2&1;
    Y1 on Y2&1;
    Y2 on Y1&1;! "Y2 on Y1&1;" for the naïve estimation; "Y2 on Y1;"
    for the model adjustment method.
    %BETWEEN%
    Y1 with Y2;
OUTPUT:
    TECH1 TECH8 STDYX;
```