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UNIVERSITY**

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**DESIGN, MEASUREMENT, AND ANALYSIS
CONSIDERATIONS AND EVALUATIONS IN
INTENSIVE LONGITUDINAL METHOD**

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SCHOOL OF SOCIAL SCIENCES

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CONSIDERATIONS AND EVALUATIONS IN
INTENSIVE LONGITUDINAL METHOD**

LIM JIE XIN

School of Social Sciences

A thesis submitted to the Nanyang Technological University
in partial fulfilment of the requirement for the degree of
Doctor of Philosophy

2021

Statement of Originality

I certify that all work submitted for this thesis is my original work. I declare that no other person's work has been used without due acknowledgement. Except where it is clearly stated that I have used some of this material elsewhere, this work has not been presented by me for assessment in any other institution or University. I certify that the data collected for this project are authentic and the investigations were conducted in accordance with the ethics policies and integrity standards of Nanyang Technological University and that the research data are presented honestly and without prejudice.

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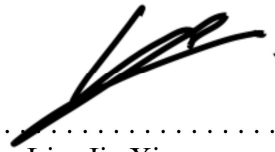
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Authorship Attribution Statement

This thesis **does not** contain any materials from papers published in peer-reviewed journals or from papers accepted at conferences in which I am listed as an author.

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Gone are the days spent frolicking,
Out by the lake crickets calling;

On a trip that seemed arduous,
Darkened sea swelling merciless;

Behold the light streaking across,
Yelling over loud waves and roars;

Engulfed by warmth of rising sun,
Nectar flows and Spring has begun;

To the souls who have meant me well,
Use these words to thank you, I shall.

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Abstract

This dissertation examined the accuracy of a few selected statistical approaches in evaluating invariance in measurement and mediation with the presence of planned-missing data in the context of intensive longitudinal method (ILM). The planned-missing data design was implemented as a three-form design where a portion of measurement scale items were selectively removed for individuals at each measurement occasion with the purpose of reducing participation burden and fatigue stemming from the burst of measurements in ILM ranging from 2 to 12 measurement occasions per day. Three simulation studies were conducted with the aim of providing insights and recommendations to applied researchers in the design, measurement, and analysis of intensive longitudinal data. Study 1 compared two methods for testing intensive longitudinal measurement invariance in their performance in detecting invariant and non-invariant measurement parameters. Study 2 and Study 3 evaluated the performance of the dynamic structural equation model (DSEM) framework in estimating the time-invariant and time-varying effects of longitudinal mediation models. Sample sizes (N), length of measurement occasions (T), percentage of planned-missing data (PMD), and effect sizes were manipulated in the simulation studies. The dissertation concluded with recommendations for applied researchers. Limitation and areas for future research were also discussed.

Chapter 1

Introduction

The intensive longitudinal method (ILM) has gained popularity over the last decade with the advancement on communication and data storage technology (Hamaker & Wichers, 2017). The ILM mainly sets itself apart from conventional longitudinal panel method in which a typical research that employs the intensive longitudinal method lasts about 1 to 2 weeks, with 2 to 12 measurement occasions per day. This approach could result in participation burden and fatigue during data collection due to multiple measurements in a short timespan (Scollon et al., 2009).

Apart from the data collection challenges, unlike longitudinal panel method, longitudinal measurement invariance has not been widely discussed in ILM. This could partly due to the unique data composition in which there may be more variables measured across the measurement occasions (T) than participants (N) which renders estimation problem in conventional longitudinal confirmatory factor analysis approach with the wide-form data (Wothke, 1993). Most recently, Asparouhov et al. (2018) has proposed the dynamic structural equation model framework as a unified method to analyse the intensive longitudinal data (ILD) as an extension to the ubiquitous structural equation model framework in social science research. As a relatively contemporary method, performance of the DSEM framework on various models (e.g., longitudinal mediation model with time-invariant and time-varying effects) and data properties (e.g., sample size, measurement occasions, and presence of missing data) have yet to

be reliably established.

1.1 Purpose and Significance of Dissertation

This dissertation proposed the inclusion of the three-form planned-missing data design as an integral part of the intensive longitudinal research design. The effect of planned-missing data on the statistical analyses of ILD was evaluated through a series of simulation studies. Competing statistical methods were adapted from existing approaches and compared to address the need for an alternative methodology for testing intensive longitudinal measurement invariance. The dissertation also aimed to evaluate the effect of sample size (N), measurement occasions (T), and percentage of planned-missing data (PMD) on the performance of the DSEM framework under different combinations of structural path effect sizes.

Through this series of evaluations, this dissertation contributes to the field of intensive longitudinal research by advancing the development of the research methodology and by providing insights and recommendations to applied researchers in the design, measurement, and analysis of ILD.

1.2 Overview of Dissertation

This dissertation is organised into 6 chapters. In chapter 2, key terminologies and past studies on the intensive longitudinal methodology relevant to the scope of this dissertation were reviewed. In chapter 3, I reported the results of a simulation study on the comparison of the accuracy of two recently developed statistical procedures in identifying measurement (non-)invariance in intensive longitudinal data.

In chapter 4, I reported the results of a simulation study on the performance of the dynamic structural equation modeling (DSEM) framework in estimating the parameters of two different longitudinal multilevel mediation models. In chapter 5, I reported the results of a simulation study on the performance of DSEM in estimating the parameters of a time-varying effect mediation model.

In chapter 6, I listed several suggestions for future research and concluded with general suggestions on intensive longitudinal research design and analysis for applied researchers based on the findings in chapter 3, chapter 4, and chapter 5.

Chapter 2

Literature Review

With current development in technology such as smart phone, wearable technologies, and cloud storage, data collection and storage has never been easier and cheaper. Such new technological development has enabled and greatly influenced the intensive longitudinal method (ILM) which has gained steady popularity over the last decade (Hamaker & Wichers, 2017). The ILM is characterised by the general research aim to study the experience, behaviour, environment, and physiology of individuals in their naturalistic environment through repeated real-time (or an approximation of real-time) observations of daily life (Conner & Mehl, 2012). ILM can be considered as an umbrella term for a range of similar research methods, such as experience sampling (Csikszentmihalyi & Larson, 1987), daily dairies, ecological momentary assessment (Stone & Shiffman, 2002), ambulatory assessment (Fahrenberg et al., 2007), and real-time data capture (Bolger & Laurenceau, 2013). Collectively, data resulting from ILM is referred to as the intensive longitudinal data (ILD; Walls & Schafer, 2006).

2.1 Intensive Longitudinal Research Method

The literature has seen an exponential growth in the utilisation of the ILM in research studies. Hamaker and Wichers (2017) noted fewer than 25 published studies in the year 1990 could be found in the PubMed database, and about 50 published paper a decade later in 2000. This was followed by a rapid growth to about 150 papers in the

year 2010 and further increased towards 400 papers by 2015.

A typical intensive longitudinal research takes about 1 to 2 weeks, with 2 to 12 measurement occasions per day (Scollon et al., 2009). This can be differentiated to some degree with the longitudinal panel method which has relatively fewer measurement occasions and the interval of each adjacent occasions are typically a least six months apart (Collins, 2006). The ILM and longitudinal panel method do not merely differ in terms of their design, but also on their intended research objectives (McNeish & Hamaker, 2020). While the longitudinal panel method aims to understand the growth trajectory of the variable-of-interest and between-individual differences in trajectory, the ILM often does not view systematic change (i.e., trends) as an important feature and its focus is on explaining the within-individual fluctuation of the variable-of-interest in a relatively stable process (McNeish & Hamaker, 2020).

ILM can be broadly categorised into three types: interval-contingent designs, signal-contingent designs, and event-contingent designs using their data collection schedule (Shiffman, 2014; Wheeler & Reis, 1991). In interval-contingent designs, participants respond at regular and predetermined interval of time (typically once or twice a day with fixed equidistance interval; Bolger & Laurenceau, 2013). In signal-contingent designs, participants respond at the point of receiving a prompt that would be sent at a random interval (typically around six prompts per day). A variation of the signal-contingent design is the pseudo-random (or block-random) protocol where time of day is defined by blocks of interval, and the prompts are delivered at random once within each block to ensure sufficient coverage (Bolger & Laurenceau, 2013; Shiffman, 2014). In event-contingent design, participants are required to respond when pre-determined events took place (Bolger & Laurenceau, 2013).

In recent years, ILM has been applied in various clinical and psycho-pharmacology research. These include investigating the effects of cognition and affect prior and after a non-suicidal self-injury attempt in individuals with borderline personality disorder (BPD; Andrewes et al., 2016), understanding the symptoms of BPD to enhance diagnostics and treatment (Santangelo et al., 2014), evaluating the associations between

temporal differences in the symptoms of anxiety disorders and their association with moods, behaviours, and situational triggers has also benefited from the use of ILM (e.g., Walz et al., 2014), investigating the baseline daily behaviour, moods, and triggers of cocaine-dependent outpatients (Epstein & Preston, 2010), and examining the affect, self-confidence and smoking urges in quitters and relapsers in tobacco smoking-cessation (Shiyko et al., 2012).

The potential application of ILM has also been discussed in the field of educational research (Zirkel et al., 2015), behavioural health research (Ginexi et al., 2014), biopsychosocial medicine research (Yoshiuchi et al., 2008), organisational research (Fisher & To, 2012), emotion research (Augustine & Larsen, 2012), personality research (Fleeson & Nofle, 2012), and developmental psychology (Hektner, 2012).

Schultzberg and Muthén (2018) found that there were no common consensus on the sample sizes and measurement occasions to be used in ILD studies. The notion that sample size used in ILD is commonly smaller than the measurement occasions may not be true based on their brief review. Table 2.1 summarises Schultzberg and Muthén’s (2018) reviews.

Table 2.1: Schultzberg and Muthén’s (2018) Review of ILD Studies

Study	Area of Research	N	T	Primary Statistical Model
McAdams and Constantian (1983)	Social Psychology	50	49	Analysis of Variance
Bolger and Schilling (1991)	Personality	339	42	Multilevel regression
Shiffman and Waters (2004)	Health Psychology	215	100	Generalised Estimating Equation
Cohen et al. (2008)	Clinical Psychology	62	7	Multilevel regression
Jongerling et al. (2015)	Emotions	89	42	Multilevel regression
Trull et al. (2008)	Clinical Psychology	60	168	Multilevel regression
Hamaker et al. (2018)	Emotions	100	100	Dynamic Structural Equation Model

Note: N = sample size; T = measurement occasions. All studies included in the table used multiple-item scale for the measurement of primary variable-of-interests.

Self-reports have been utilised extensively in psychological research and the acceptance of self-report as a reliable research methodology in measuring individuals’ thoughts, feelings, and behaviours is based on the assumption that respondents are able to recall and report the information without bias (Schwarz, 2012). A key benefit of using ILM is the ability to collect data in (approximately) real-time and hence the cognitive bias and the limitation of human cognitive make-up can be alleviated, or at least minimised in self-reports with the use of ILM. However, respondent burden was listed

as one of the challenges of ILD and using a smaller number of items in each measurement occasion to reduce burden has been recommended (Scollon et al., 2009).

To avoid respondent burden, ILM studies have used single-item measurement such as the measurement of mood where individuals were asked to rate a mood adjective (e.g., angry, sad, and anxious) on a likert-type scale (e.g., Chue et al., 2017; Houben et al., 2017; Shiyko et al., 2017). Even though single-item measurement could alleviate the burden on the respondents, the choice of using a single-item measurement may lower the reliability of the measurement. To reach an balance between participation motivation and research quality, a planned-missing data design may be considered.

2.2 Planned-Missing Data Design

Longitudinal studies have long employed some form of planned-missing data design (PMD) to balance between research budget and efficiency of statistical test (Wu et al., 2016). This implementation of the PMD can also reduce burden on participants (Enders, 2010) which may stem from perceived concerns on content sensitivity of the items, the number of measurement occasion, and especially, the length of questionnaire (Plewes, 2016). With the implementation of PMD in longitudinal studies, incomplete data is collected from participants in a planned manner using one or a combination of these three methods: randomly assigning partial questionnaire (matrix sampling design), or partial measurement occasion (wave missing design), or administering an accurate but expensive measurement on a small subset of the sample and a less accurate but inexpensive measurement on the whole sample (two-method measurement design; Graham et al., 2006; Little & Rhemtulla, 2013). This dissertation focused on the matrix sampling design for its ease of implementation.

Matrix sampling (or multiple matrix sampling; Shoemaker, 1971), also referred to as item-sampling (Lord, 1962), is a measurement-focused efficiency design that have been used in survey (e.g., Gonzalez & Eltinge, 2007) and educational testing (e.g., Gonzalez & Rutkowski, 2010). Matrix sampling involves splitting questionnaires into

shorter subsets of questions (i.e., forms), with possible overlapping items between each form, and administer each form to random samples of the population (Gonzalez & Rutkowski, 2010; Graham et al., 2006; Merkouris, 2015; Shoemaker, 1971). In the educational testing context, application of matrix sampling can ensure sufficient content coverage while maintaining a reasonable administration duration so as to not increase burden on the examinee and testing time (Gonzalez & Rutkowski, 2010).

Two concerns in the implementation of the matrix sampling design are the allocation of items into distinct forms, and the allocation of forms to samples (Jorgensen et al., 2014; Plewes, 2016). One popular matrix sampling design used in psychological research is the three-form design (e.g., Graham et al., 2006; Little et al., 2014). In this design, items from questionnaires are split into 4 non-overlapping item blocks (i.e., an anchor block X, and A, B, and C block). The anchor block is recommended to contain demographic items and key items from questionnaires (as determined qualitatively using item content or quantitatively using factor loadings) and the other items are to be distributed evenly across the other 3 blocks (Little & Rhemtulla, 2013). Each participant would receive one of the three forms that are made up of a combination of the anchor block (X) and either the A, B, or C block. Items in the anchor block usually appear before the other item block in each form, and the order of each non-anchor block is partially counter-balanced, where each block would appear last in at least one form [e.g., XAB (Form 1); XCA (Form 2); XBC (Form 3)] though this is not a requirement (Graham et al., 2007). Usually each block in the three-form design would consist of about 25% of the total number of items, therefore each form will consist of about 75% of the total item, hence the three-form design will introduce 25% to 30% of missing data into the dataset (Little et al., 2014). Variation of the three-form design has also been proposed to include more blocks in the design to further shorten each form (e.g., each form only contains 40% of the overall items; Raghunathan & Grizzle, 1995).

2.2.1 Form Assignment Method

When the three-form design is used in the research that measures participants in multiple measurement occasions, researchers would need to make a decision on how to assign the different forms to each participant at different measurement occasions: should the participants receive the same form over these measurement occasions (e.g., Form 1 throughout the study for a particular individual), or should different forms be administered at different occasions, and should this assignment be random or cycle through the forms systematically (e.g., Form 1 at Time 1, Form 2 at Time 2, Form 3 at Time 3, and so on for a particular individual?) Jorgensen et al. (2014) has suggested that, in general, systematically assigning different forms over time for each individual would be more statistically efficient in terms of model estimation (i.e., precision of parameter estimate is comparable between the conditions with complete data and planned-missing data) under the assumption that the items have sufficient reliability and it would also ensure that most items are not repeated in close proximate measurement occasions hence alleviating practice effects.

2.2.2 Impact of Planned-Missing Data on Model Estimates

Rubin (1976) has provided a taxonomy of mechanisms that describes the theoretical relationship between observed variables and the probability of being missing, namely missing completely at random (MCAR), missing at random (MAR), and missing not at random (MNAR). When data are MAR, the probability of missing data on a variable is *not related* to the value of the variable itself, but it is a function of other measured variable(s) in the dataset. When data are MNAR, the probability of missing data on a variable is *related* to the value of the variable itself, after controlling for other measured variable(s) in the dataset (Enders, 2010).

In contrast to MAR and MNAR, the implementation of PMD would result in a dataset with data-points that are missing completely at random (MCAR). The assumption of MCAR mechanism is more stringent than the MAR mechanism. When the data is MCAR, the probability of missing data on a variable is *neither* related to the value of

the variable itself nor other measured variable(s) in the dataset. That is, MCAR mechanism has a strict assumption that the missing-ness is unrelated to the data (Enders, 2010). Collectively the MCAR and MAR mechanisms are referred to as ignorable missing-ness because modern state-of-the-art methods such as full-information maximum likelihood (FIML) and multiple imputation can be used to handle such data (see Schafer & Graham, 2002, for a review). The Bayesian approach can also be utilised to optimally analyse dataset with ignorable missing data (Asparouhov et al., 2018; Lee, 2007).

In general, PMD would only affect the precision of estimation and therefore decrease statistical power in testing parameter estimates (i.e., the probability of rejecting a null hypothesis in the presence of a non-zero effect) with the use of the appropriate methods to handle the missing data (e.g., FIML or Bayesian method; Enders, 2010). Nevertheless, the lack of statistical power can be recovered by increasing the sample size (Enders, 2010); however, the number of sample size that is required for the recovery also depended on the complexity of the model that is being tested (Jia et al., 2014).

2.3 Measurement Invariance

The literature on longitudinal panel research have argued that measurement invariance of measured constructs need to be addressed regardless of the type of analysis that involves data collected from more than one time point (e.g., Little, 2013). Even though responses on questionnaires are collected in multiple occasions in the intensive longitudinal research, the issue of measurement invariance has not been discussed extensively. Assumption of invariance has to be tested to ensure that the measurement is on the same metric at each measurement occasion (Widaman et al., 2010). If such assumption is not met, any conclusion about between-time differences or change in the constructs is not substantial (Meredith, 1964).

Meredith (1964, 1993) argued from the statistical point-of-view that non-invariance in measurement across group or time would occur when the error variance of the indi-

cators (i.e., items) are affected systematically and in turn the indicators will not have the same relationship among themselves across group or time. The potential causes of non-invariance in longitudinal research could come from both the internal state and external conditions of the individual such as experience and environment where the individual resides (Little, 2013). Specifically, in empirical research, measurement non-invariance would be observed if a response shift occurred in at least one of the measurement occasions (Howard et al., 1979). Response shift may occur due to change in experience (e.g., before and after an intervention or treatment) if the individuals reconceptualise (i.e., a change in the interpretation of the item or construct), reprioritise (i.e., a change in the perceived importance of the item in relation to the construct), or recalibrate (i.e., a change in the internal standard for comparison) the measurement (Schwartz & Sprangers, 1999; Wilson, 1999). Reconceptualisation and reprioritisation would lead to the non-invariant of factor loading patterns across time; while recalibration would lead to non-invariant of the intercept (Oort, 2005).

Measurement invariance is commonly tested using multi-group confirmatory factor analysis for independent groups; while a typical confirmatory factor analysis is more routinely used to test for measurement invariance for longitudinal data. Recent development in the measurement invariance methodology has introduced the Alignment method (Asparouhov & Muthén, 2014) and the cross-classified factor model (Muthén & Asparouhov, 2012) as alternatives to the traditional methods. These methods are introduced in the following section.

2.3.1 Multi-group CFA Method

The traditional method to test for measurement invariance is through the application of the multiple-group confirmatory factor analysis framework (MG-CFA) using a progressive model-fitting process commonly starting from the least restrictive models to more constrained models (Millsap & Olivera-Aguilar, 2012). Readers should note that the term "group" is used flexibly to represent demographic groupings such as gender or ethnicity. In the context of this dissertation, "group" is used interchangeably with

"time" to refer to measurement occasions in longitudinal research (i.e., data collected at each measurement occasion can be considered as a distinct "group" of observations).

Using a three-item single-factor model modelled at three measurement occasions as illustration of the MG-CFA (see Figure 2.3.2), the Y_{jt} represents the item (where j refers to the item number and t refers to the measurement occasion when the items were measured). α_t and ψ_t are the mean and variance of the latent factor η_t , while τ_{jt} and λ_{jt} represent the item intercepts and loadings. Note that the vertical dotted lines separating the three measurement occasions (grouping-unit) are physical representation of the independence assumption of the observed and latent variables between the grouping-unit that is placed on the MG-CFA method.

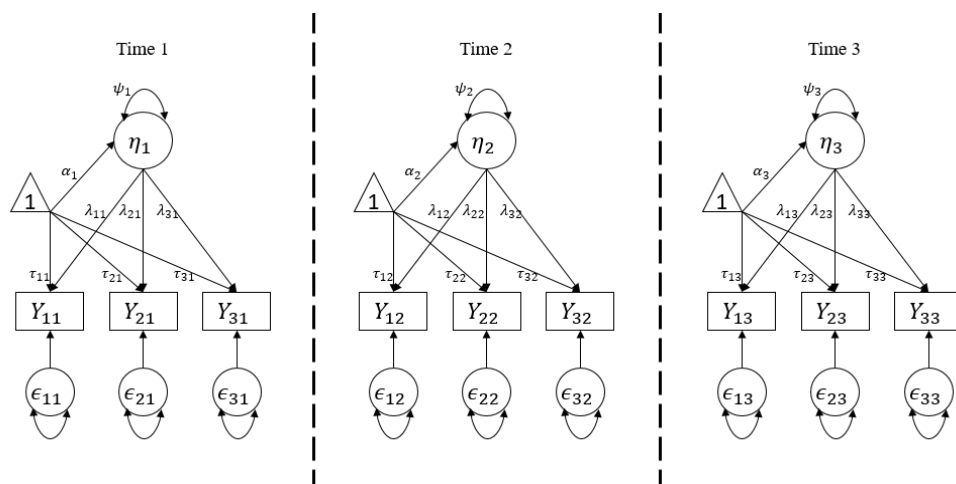


Figure 2.3.1: Multi-Group Confirmatory Factor Model

A typical procedure to test measurement invariance with MG-CFA follows four main subsequent steps as outlined by Widaman and Reise (1997): (1) equivalence of factor structure (configural invariance); (2) equivalence of factor loadings (metric invariance); (3) equivalence of intercept (scalar invariance); (4) equivalence of item residuals (strict invariance). Evidence of equivalence is obtained via the goodness-of-fit indices commonly used in structural equation modeling. Configural invariance is concerned with establishing the equivalence of the measurement model factor structure

across the grouping-unit.

If the configural invariance shows an acceptable model-data fit, equality constraints on the factor loadings will be imposed to test the metric invariance. With reference to the Figure 2.3.2, factor loadings across the grouping-unit would be constraint to be equal as $\lambda_{11} = \lambda_{12} = \lambda_{13}$, $\lambda_{21} = \lambda_{22} = \lambda_{23}$, and $\lambda_{31} = \lambda_{32} = \lambda_{33}$. On top of using the goodness-of-fit indices, a nested modal comparison between the configural invariance model and the metric invariance model can be done to test the change in the data-model fit between the two models. The metric invariance is established if the change in data-model fit does not reach the pre-specified statistical significance level.

Once the metric invariance has been established, additional equality constraints on the intercepts will be imposed to test the scalar invariance. With reference to the Figure 2.3.2, the additional equality constraints are $\tau_{11} = \tau_{12} = \tau_{13}$, $\tau_{21} = \tau_{22} = \tau_{23}$, and $\tau_{31} = \tau_{32} = \tau_{33}$. The criterion of establishing metric invariance is the same as the criterion used for the scalar invariance. Once the scalar invariance has been established, the strict invariance can be tested with the same procedure. However, researchers would typically omit the testing of strict invariance for most application (Putnick & Bornstein, 2016). It is also common to establish partial invariance when scalar invariance cannot be obtained. Partial invariance is established by partially relaxing the equality constraints on selected intercept and/or loadings parameters (Putnick & Bornstein, 2016).

Even though the MG-CFA method is conventionally used to establish the evidence of measurement invariance, the method is impractical to be applied on data with many grouping-units as a lack of model-data fit is commonly encountered even when there were only minor differences in the parameters between the units (Muthén & Asparouhov, 2016). On top of that, the process to establish partial measurement invariance requires multiple inspection of the modification indices and subjective model re-specifications in MG-CFA method ((Muthén & Asparouhov, 2014). Moreover, application of the MG-CFA in longitudinal data that involves treating time as a grouping-unit would lead to a major violation of the independent assumption on the grouping-unit imposed by the MG-CFA method (e.g., Templin, 2012).

An alternative approach to establish longitudinal factor model that does not utilize the multi-group approach is the longitudinal confirmatory factor analysis model. Under this framework, the independent assumption of data between time can be relaxed and the dependencies between factors and items across time can be modelled explicitly.

2.3.2 Longitudinal CFA Method

Under the longitudinal confirmatory factor analysis (CFA) model framework, the correlation between factors across time can be modelled explicitly, and measurement error of the same items are allowed to correlate across measurement occasions. A graphical representation of this longitudinal CFA model is depicted in Figure 2.3.2, which is in contrast with the MG-CFA method in Figure 2.3.2 by the addition of the double headed arrows to represent the covariances between the factors (η_t) and item residuals (ϵ_{jt}) across time to account for the non-independence. Researchers have argued for the use of longitudinal CFA method over MG-CFA method to test for longitudinal measurement invariance because the data would not be independent across time thus would be a violation of the assumption of independent grouping of the MG-CFA approach (e.g., Templin, 2012).

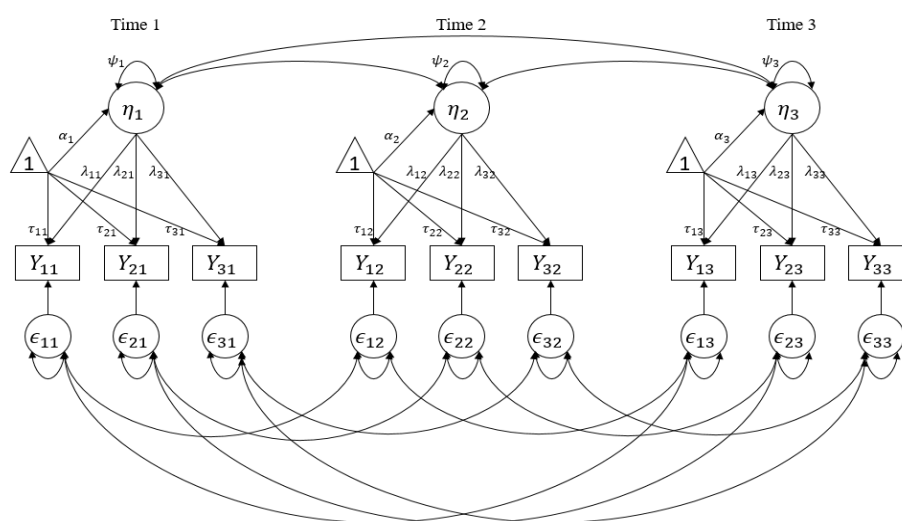


Figure 2.3.2: Longitudinal Confirmatory Factor Model

Even though the model to test longitudinal measurement invariance in this approach is slightly different from the multi-group approach, the logic and procedure of testing for measurement invariance is in close parallel (Little et al., 2007; Liu et al., 2016; Widaman et al., 2010). The configural invariance model specifies the same pattern of factor loadings over time and all parameters are freely estimated (except for parameters that are required to be constraint for model identification). The metric model imposes an equality constraint on the factor loadings across time. The scalar invariant model constraints both factor loadings and intercepts to be equal across time. The covariance of the error variances could also be constraint to be equal for further testing (Liu et al., 2016).

Even though the longitudinal CFA method is more suitable for testing longitudinal measurement invariance than the MG-CFA method, the longitudinal method may be impractical when there are more variables (columns) than individuals (rows) in the multivariate data layout, such as the intensive longitudinal data, that is required for the implementation of the longitudinal CFA. This will result in a non-positive definite sample variance-covariance matrix which will hinder the model parameter estimation process (Wothke, 1993).

2.3.3 Alignment Method

Responding to the need for a more efficient method to enable latent mean comparison across groups in cross-country/culture comparison research, Asparouhov and Muthén (2014) proposed the Alignment method, which is an automated procedure built on top of the configural model to achieve an approximate measurement invariance in the measurement model. The alignment method has been implemented since Mplus v7.11 in the mixture modelling framework. The basis of the alignment method is essentially a single-class mixture model, with the grouping-unit being a latent class variable. The alignment method is fundamentally the same as the multi-group model because the latent class variable can, in fact, be deduced by the observed grouping-unit (Asparouhov & Muthén, 2010).

The goal of the Alignment method is to estimate the group-specific factor means and variances with an approximate group-invariant measurement parameters (i.e., intercept and factor loadings). Much akin to the application of rotation in exploratory factor analysis (EFA) in that the model-data fit would not be affected by the rotation procedure, the alignment method produces a final set of parameter estimates that has the same data-model fit as a configural model through the optimisation of a loss function to maximize a few large non-invariant parameters and retain other parameters as mostly invariant (Asparouhov & Muthén, 2014).

The following paragraph provides a summary of the alignment method as described in Asparouhov and Muthén (2014). The alignment method first fits a configural model where parameters are freely estimated across group, with factor variance η fixed as 1 and factor mean α as 0 in all groups. The alignment algorithm then searches for a unique final set of factor mean and variance parameters for each group that minimises a total loss function F as defined as

$$F = \sum_j \sum_{g_1 < g_2} W_{g_1 \cdot g_2} * [f(\tau_{jg_1,A} - \tau_{jg_2,A}) + f(\lambda_{jg_1,A} - \lambda_{jg_2,A})] \quad (2.1)$$

The differences between the intercepts (τ) and loadings (λ) of the j^{th} item for each pair of groups (g) contribute to the total loss function in Equation 2.1 via a component loss function $f(x)$, where $f(x) = \sqrt{\sqrt{x^2 + 0.01}}$. The component loss functions are weighted using the sample sizes of the group-pairs via $W_{g_1 \cdot g_2} = \sqrt{N_{g_1} N_{g_2}}$.

The aligned intercept $\tau_{jg,A}$ and loading $\lambda_{jg,A}$ parameters are transformed from the initial configural model intercept $\tau_{jg,C}$ and loading $\lambda_{jg,C}$ based on the relationship between factor mean and variance and the intercepts and loadings

$$\begin{aligned} Var(Y_{jg}) &= \lambda_{jg}^2 \eta_g = \lambda_{jp,C}^2 \\ E(Y_{jg}) &= \tau_{jg} + \lambda_{jg} \alpha_g = \tau_{jg,C} \end{aligned} \quad (2.2)$$

Equation 2.2 can be re-expressed as the following with respect to $\tau_{jg,C}$ and $\lambda_{jp,C}$

$$\begin{aligned}\lambda_{jp,C} &= \lambda_{jg} \sqrt{\eta_g} \\ \tau_{jg,C} &= \tau_{jg} + \frac{\lambda_{jp,C}}{\eta_g} \alpha_g\end{aligned}\tag{2.3}$$

Using the expressions in Equation 2.3, the aligned intercept $\tau_{jg,A}$ and loading $\lambda_{jp,A}$ can be obtained by

$$\begin{aligned}\lambda_{jp,A} &= \frac{\lambda_{jp,C}}{\eta_g} \\ \tau_{jg,A} &= \tau_{jg,C} - \frac{\lambda_{jp,C}}{\eta_g} \alpha_g\end{aligned}\tag{2.4}$$

To identify the factor mean and variance parameters α_g and η_g for the total loss function F during the minimisation process, either the Fixed or Free alignment optimisation method can be used. On top of constraining $\prod \eta_g = 1$, the Fixed alignment optimisation method constrains $\alpha_{g1} = 0$, while the Free alignment optimisation method estimates all α_g . When there are more than 2 grouping units (e.g., time) and if measurement non-invariance is present, the Free alignment optimization method is preferred over the Fixed alignment optimisation method (Asparouhov & Muthén, 2014).

Simulations have shown that the alignment method performs well except in cases of small group sizes or when a large amount of non-invariant parameters is present (Muthén & Asparouhov, 2016). Aside from the comparison of latent factor means and variances, the alignment method can also be used to identify the measurement parameters (i.e., intercepts and factor loadings) that are non-invariant across grouping units (e.g., measurement occasion) using an ad-hoc pairwise comparison. The ad-hoc comparison algorithm was described in Asparouhov and Muthén (2014) and is summarised in the next paragraph.

The objective of the ad-hoc comparison algorithm is, for each measurement model parameter (i.e. intercept or loadings), to construct an invariant set and a non-invariant set. The invariant set consists of a set of parameter (e.g., intercept of the same item across grouping-units) that are not statistically significantly different from the weighted-

average (by grouping-unit size) of that parameter within the set. The non-invariant set contains a set of parameters that are statistically significantly different from the weighted-average of the parameter of the invariant set. The invariant set is first created by conducting a pairwise comparison of the parameter of interest among the grouping-units using a restrictive Type I error rate (i.e., $\alpha = 0.01$). The same item parameters from different grouping-units which differences do not reach the significance-level are considered as members of the same set. The set with the largest member of units is initiated as the starting invariant set.

The weighted-average of the parameter in the invariant set is calculated, and the corresponding parameter from each grouping-unit is compared to this weighted-average at an even restrictive Type I error rate (i.e., $\alpha = 0.001$). For grouping-units that are already a member of the invariant set, if it is statistically significant different from the weighted-average, the grouping-unit is removed from the invariant set. Grouping-unit that are not a member of the invariant set and also not statistical significantly different from the weighted-average is included in the invariant set. This process is iterated until there is no more change of the invariant set membership.

2.3.4 Cross-Classified Factor Model Method

Muthén and Asparouhov (2012) suggested the application of a cross-classified factor model to model time-varying intercept and loadings parameters in a measurement model. Borrowing the terminology from the analysis of variance (ANOVA) framework, supposed the individual and measurement occasions are two factors with each subject and time-unit as levels of the factors, each observation is nested under the crossing of the levels. Linking the terminology to the cross-classified model framework, the observations belong to the within-level of the data structure, while the individual and measurement occasion "factors" belong to the between-levels. Therefore, similar to ANOVA, a cross-classified model is able to model the effects of the "factors" at the corresponding between-levels.

Time-varying intercepts and loadings can be estimated in a cross-classified factor

model by modelling as random effects at the between-time level. Figure 2.3.3 illustrates a cross-classified three-item single-factor model with random intercept and loadings at the between-time level. The each random effect is modelled as a random normal variable using a mean (e.g. λ_1) and variance parameter (e.g. $\sigma_{\xi_{\lambda_{t1}}}^2$). For example, $\lambda_{1,t}$ represents factor loadings of the 1st item and it is specified as a random loading with a mean and variance at the between-time level. The mean (λ_1) represents the average value of the parameter across time and the variance ($\sigma_{\xi_{\lambda_{t1}}}^2$) represents the amount of variability of the parameter across time. The variance of the latent variable (η_i^B) can also specified at the between-individual level to model the dependency of η_{it} within individual (Muthén & Asparouhov, 2012).

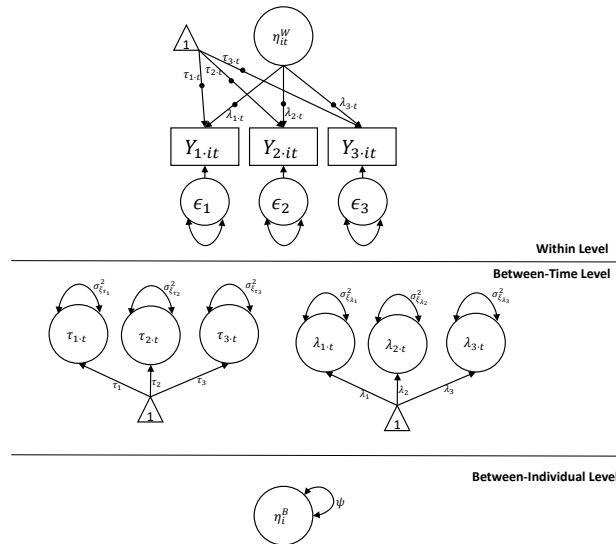


Figure 2.3.3: Cross-Classified Factor Model

The presence of non-invariance parameter across time can be evaluated by testing the variance of each of the random intercepts and loadings at the between-time level. Variance that deviates statistically different from the null value of 0 could be taken as evidence of that the parameter is time-varying. To the best of my knowledge, this method of identifying the presence of non-invariant measurement parameters has not been evaluated nor widely used in the literature yet.

2.4 Intensive Longitudinal Data Modeling Frameworks

Collins (2006) argued that an integration of the theoretical model, temporal design, and statistical model are necessary for longitudinal research to effectively answer any research question. More specifically, a theoretical model of longitudinal research should describe the pattern of change of the phenomenon of concern. The temporal design of the study (e.g., timing, frequency, and, interval of observations) should correspond to the theoretical expectation of the change. The statistical model should also match the theoretical model to correctly operationalise the change process using the data collected through the corresponding temporal design (Collins, 2006).

ILD can be modelled using the multilevel regression model and the multilevel structural equation model, to name a few, which are routinely used for traditional longitudinal panel data in the social science [also see Walls and Schafer (2006) for a review]. A new statistical modelling framework, the dynamic structural equation model (DSEM; Asparouhov et al., 2018) has been introduced recently based on the ubiquitous structural equation modelling framework for the modelling of ILD. These methods are briefly introduced in the following section with a focus on the dynamic structural equation model (DSEM).

2.4.1 Multilevel Regression Model

The mixed-effect model is one of the more popular methods in modelling ILD because of its ability to handle nested structure in the data (i.e., repeated observations nested within individual). The mixed-effect model (Littell et al., 1996) is also known as the random coefficient model (de Leeuw & Kreft, 1986), the hierarchical linear model (HLM Raudenbush & Bryk, 1986), or the multilevel linear/regression model (MLM; Bryk & Raudenbush, 1987). These terms will be used interchangeably despite the fact that they arguably are not exactly the same albeit sharing similar features (Hox, 2010). ILD can be viewed as having a multilevel structure with the repeated-measures nested (level-1 unit) within individuals (level-2 unit), forming a two-level HLM model (Hox,

2010). The model was promoted as a suitable method for the analysis of ILD in Bolger and Laurenceau (2013) and has been applied in contemporary empirical papers (e.g., Cohen2008, Jongerling2015, Trull2008).

The MLM is also referred to as the slope-and-intercept-as-outcomes regression, where the slope and intercept of the level-1 (within-level) equation is treated as the outcome of the level-2 (between-level) equations. However, implementation of such model in the traditional multilevel regression model framework has its own limitations. The inability of MLM to utilise latent measurement variable to partial out measurement error from the observed variables is a primary critique of the modelling approach, on top of the absence of a global model-fit statistics within this modelling framework (Kline, 2015). The MLM is also a univariate model by nature that only a single outcome variable can be modelled which may be limiting for certain research questions that involve multiple outcomes.

2.4.2 Multilevel Structural Equation Model

The multilevel structural equation model (MSEM) has been developed as an integration of MLM and structural equation model as early by Schmidt (1969) Schmidt (1969), and later by Muthen (1989) and Rabe-Hesketh et al. (2005). In general, while the MLM can only model relationship between observed variables, the MSEM method makes it possible to specify latent measurement model in the multilevel model. The capability to include a measurement model can address the assumption of perfect-reliable measurement in MLM, and at the same time still able to implement the slope-and-intercept-as-outcomes model as described in the previous section using both observed and latent variables (Kline, 2015; Rabe-Hesketh et al., 2012). By virtue of an extension of the structural equation modelling framework, the MSEM can easily accommodate multiple outcomes in the model.

Conventional fit statistics and some of the goodness of fit indices have been used in typical SEM analysis are also available for evaluating MSEM. On top of that, MSEM has an advantage over non-structural equation modelling method for handling missing

data in both the measurement and structural model in conjunction with modern missing data analysis method (Muthén et al., 1987). MSEM is a special case of the dynamic structural equation modelling (DSEM) framework described in the next section, therefore MSEM is not further elaborated in this section.

2.4.3 Dynamic Structural Equation Model

More recently, Asparouhov et al. (2018) proposed the dynamic structural equation model (DSEM) framework that combines time-series modelling, multilevel modelling, structural equation modelling, and time-varying effect model to allow flexibility in modelling the features of ILD (e.g., autoregressive relationships, temporal trends and cycles, and time-varying relationships). The most general DSEM is the cross-classified DSEM model which allows the specification of individual- and time-varying effects; a more restrictive model is the two-level DSEM which allows the specification of individual-varying effects; while the most restrictive model is the single-level DSEM that is equivalent to a single-case time-series model (Asparouhov et al., 2018). As a general modelling framework, the DSEM is able to accommodate multiple continuous and categorical variables as predictors and outcomes in the model. The DSEM framework is currently implemented in the Mplus (since the 8th version) general latent variable modelling software commonly used in social sciences.

As with multilevel modeling, the within-individual (level-1) variables are commonly mean-centered to improve the interpretation of the model parameters (McNeish & Hamaker, 2020). Similar to MSEM, the DSEM uses latent individual-mean centering, as opposed to observed individual-mean centering commonly applied in MLM, for the variables in the modelling of level-1 and level-2 (between-individual) structural paths. Asparouhov et al. (2018) has shown that the latent mean centering is superior than the observed mean centering in that the former prevents the bias in autoregressive parameter estimates (i.e., Nickell's bias) and the bias in the level-2 structural paths (i.e., Lüdtke's bias).

The term "dynamic" in DSEM refers to the moment-to-moment instantaneous changes

in variables which is a common component in the time-series modelling of ILD that is characterised by autoregressive relationships (McNeish & Hamaker, 2020, e.g., relationship between variable measured at time t and $t - 1$). The Mplus software implementation of the DSEM framework introduces specialised functions to aid in the creation of lagged variables (via the `LAGGED` function in the `VARIABLE` command for observed variables) and specification of autoregressive relationship between variables (via the `&` function in the `MODEL` command) and residuals (via the `^` function in the `MODEL` command) that are not available for the MLM and MSEM framework (Asparouhov et al., 2018), though these variables and relationship could still be manually created and specified in the latter two models.

The DSEM is a discrete-time modelling framework [as opposed to continuous-time modelling, see Voelkle et al. (2012) for a discussion] hence the time intervals between adjacent measurements need to be explicitly specified in the data and the interpretation of the autoregressive parameter depends on the specified interval (McNeish & Hamaker, 2020). In practice, the modelling of autoregressive relationships in DSEM requires the interval of time-adjacent measurements to be roughly equal. No additional pre-processing of the dataset is required if the data-collection design meets this requirement (e.g., interval-contingent designs). However, for ILD which measurement intervals are unequal (e.g., signal-contingent designs), the data requires pre-processing to align the data on a common time-grid by means of appending missing observations in the dataset so that the autoregressive parameter can be correctly estimated and interpreted.

To illustrate the latter scenario, imagine three consecutive measurements in an ILD taken at 10 a.m., 11 a.m., and 3 p.m., and the lag-1 autoregression between the three measurements were specified (see Figure 2.4.1). In the upper panel, the interval between time 1 (10 a.m.) and time 2 (11 a.m.) is an hour but the interval between time 2 (11 a.m.) and time 3 (3 p.m.) is four times longer than the previous interval; however, the autoregression parameters would be constrained to be the same in DSEM (i.e., $\phi = \phi'$) because the model assume the intervals between the measurements are equally

spaced.

To accommodate the unequal measurement interval, Mplus can pre-process the data (via the `TINTERVAL` function in the `VARIABLE` command) to align the measurement on a time-grid (see bottom panel of Figure 2.4.1 which uses a time-grid of 1-hour interval) by inserting missing data for the unobserved time-point on the grid (represented as squares with broken lines). This ensures the proper estimation and interpretation of the autoregressive parameters (McNeish & Hamaker, 2020). Asparouhov et al. (2018) suggested that the choice of interval of the time-grid to be driven by three considerations: interpretability of the time-interval (e.g., a natural time-unit of hours may be more interpretable than a time fraction of 2.3 hours), the amount of missing data resulting from the choice of interval, and the approximation of the actual measurement schedule (e.g., a 1-hour interval is more suitable when most measurements were taken 1-hour apart as compared to when measurements were taken 0.5-hour apart). Given an ILD with random and unequal measurement that spreads out along the time-continuum, DSEM, which is a discrete-time model, can approximate a continuous-time modelling framework by choosing a time-grid with smaller interval (Asparouhov et al., 2018).

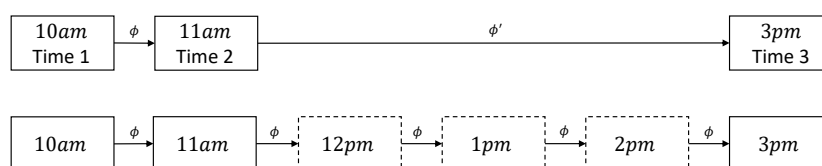


Figure 2.4.1: Unequal Measurement Intervals and Lag-1 Autoregressive Effect with 1-hour as Grid Interval

An important application of the DSEM framework is its ability to model time-

specific random effect which translates to a time-varying effect model (TVEM). The application of TVEM facilitate the testing of change in association between variables over time. A TVEM model can specify and test the varying relationship between variables across time, which is in contrasts to the typical modelling of time-invariant relationship between variables with two-level MLM or MSEM. Furthermore, even though it is possible to model time-varying effect in MLM or MSEM by modelling the interaction between a time variable and the predictor (i.e., effect of predictor on outcome depends on time), the function form of the time-varying effect (i.e., shape of the change of the parameter over time) is constraint to maintain a pre-specified parametric form (e.g., linear, quadratic, and cubic) and more complex form may be difficulty to specify (Tan et al., 2012). TVEM, on the other hand, does not have the restriction on the functional form. TVEM is implemented using the cross-classified DSEM model where random effects of individual and time can be specified, hence avoiding the need to specify the function form. The cross-classified factor model described in subsection 2.3.4 is a special application of TVEM without structural parameters.

The flexibility of the DSEM framework in fitting complex models with presence of missing data is made possible using the Bayesian method (Asparouhov et al., 2018; Hamaker et al., 2018). Interested readers can refer to the Appendix A and Appendix B for a brief introduction to the Bayesian framework and its implementation in Mplus respectively.

At the time of this writing, there were only a proof-of-concept paper with limited simulation studies (i.e., Asparouhov et al., 2018) and an evaluation research on DSEM focusing on random intercept, slope, and residual as predictors and outcomes (i.e., Schultzberg & Muthén, 2018). Given that the DSEM is a relatively new methodology for the analyses of ILD, more simulation studies have to be done to investigate the framework to understand potential limitations on a variety of models and to bolster the confidence in the adoption of the analysis framework.

2.5 Summary

This chapter reviewed key concepts and issues on design, measurement and analysis on data collected from intensive longitudinal studies in a general perspectives. This dissertation aimed to focus on three aspects of the intensive longitudinal methodology: the design, measurement, and analysis of intensive longitudinal data (ILD) that require urgent investigation. Specifically, the main interest was the implementation of planned-missing data realised by a 3-form design during data collection and its impact on the modelling of ILD. The dissertation focused on testing longitudinal measurement invariance using the alignment method and cross-classified factor model (Study 1) and modelling time-invariant (Study 2) and time-varying (Study 3) longitudinal mediation process. Relevant past research specific to each of the study in this dissertation were further discussed in the corresponding chapters to facilitate reading.

2.5.1 Research Questions

The traditional method of testing longitudinal measurement invariance may not be feasible with ILD due to the challenges in assumption violations and estimation mentioned in the previous sections. Instead, this dissertation focused on two recently developed methods, namely the alignment method and the cross-classified factor model, and compared their performance in detecting measurement (non-)invariance in data simulated as intensive longitudinal data with planned missingness. The research questions of Study 1 were

- Which method provides a higher accuracy rate in identifying invariant and non-invariant measurement parameters?
- What are the impact of planned-missing data, sample size, and measurement occasion on the accuracy rate?

The evaluation of the DSEM framework has been limited due to its relatively new development. The performance of the DSEM framework in modelling ILD and testing

longitudinal mediation process were evaluated in Study 2 and 3. The mediation model was chosen for its ubiquitous use in understanding psychological process.

The research question of Study 2 was

- What are the impact of planned-missing data, sample size, measurement occasion, and effect size on the parameter estimates of the *time-invariant* mediation model parameters?

While the research question of Study 3 was

- What are the impact of planned-missing data, sample size, measurement occasion, effect size, and measurement reliability on the parameter estimates of the *time-varying* mediation model parameters?

The research questions are further detailed in their respective chapters. The findings from this dissertation can be used to inform applied researchers who wish to adopt the intensive longitudinal methodology in their field of research.

Chapter 3

Study 1

Comparison of the Alignment Method and Cross-Classified Factor Model for Testing Intensive Longitudinal Measurement Invariance in the Presence of Planned-Missing Data

Longitudinal measurement invariance has to be established to facilitate the modelling of longitudinal differences and change (Meredith, 1964). This is to ensure that the measurements are on the same metric between the measurement occasions (Widaman et al., 2010). Non-invariance in measurement parameters over time may occur due to response shift (Howard et al., 1979) which may be triggered by change in internal psychological state or external experience (Schwartz & Sprangers, 1999; Wilson, 1999). In the context of intensive longitudinal method, the measurement taken before and after a specific event (e.g., smoking cessation intervention programme) or time-point (e.g., working hours) may induce a response shift. Therefore, in order to empirically test for the occurrence of response shift, intensive longitudinal measurement invariance has to be tested to ensure the parameters remain equivalent over time to facilitate subsequent modelling.

The traditional longitudinal approach of testing longitudinal measurement invariance with a wide-format multivariate data is not feasible in the context of the intensive longitudinal data due to the nature of the data, in that there are typically more variables

(columns) than individuals (rows), that will result in estimation challenges due to a non-positive definite matrix of the sample variance-covariance matrix (Wothke, 1993).

Considering that the Alignment method and the cross-classified factor (time-varying effect) model are two alternative methods to test for measurement invariance that overcomes the estimation issue as discussed in chapter 2, Study 1 investigated the two methods in their accuracy in identifying parameters that are (non-)invariant in intensive longitudinal measurement data. To the best of my knowledge, the application of these two methods have not been compared in the literature.

3.1 Objectives

The objective of the study was to investigate the application of the alignment method (Asparouhov & Muthén, 2014) and compare it with the cross-classified factor model to identify longitudinal non-invariance of factor loading and intercept parameters of a measurement model under the presence of planned-missing data. A time-invariant parameter is a parameter which population value does not change across time; while a time-varying (non-invariant) parameter is a parameter which population value changes across time (i.e., deviates from the corresponding invariant parameter). The number of parameters being correctly labelled as invariant or non-invariant by the two methods was the primary interest of this study.

3.2 Method

This study used Asparouhov and Muthén's (2014) design as the primary reference. A single-factor measurement model with five continuous indicators was used to simulate the ILD (see Figure 3.2.1).

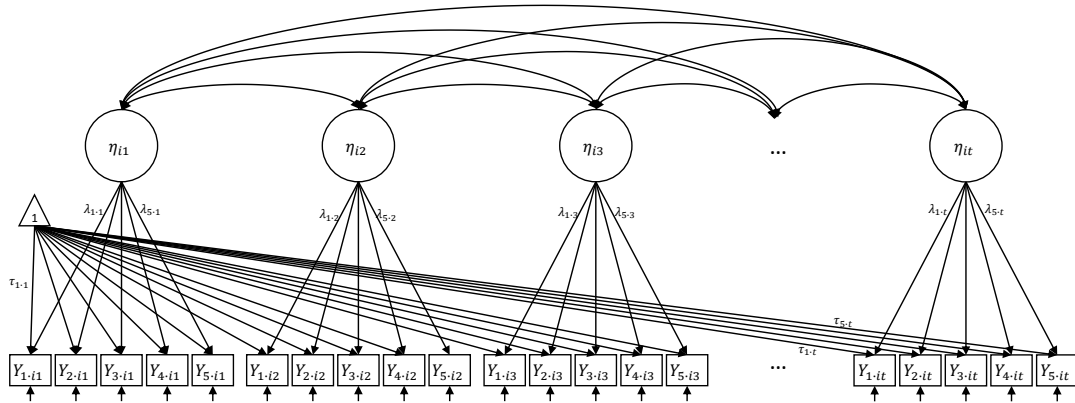


Figure 3.2.1: Data-Generating Measurement Model

3.2.1 Design

For all measurement occasions, measurement error variance (θ) was set to 1 for all indicators, while the time-invariant factor loadings (λ) and intercepts (τ) were set to 1 and 0, respectively. The latent factor (η) follows a standard normal distribution $N(0, 1)$ for all measurement occasions. The non-invariant parameters were simulated using the following three intercept-loading parameter-pairs. Pair 1: $\tau_5 = 0.5$, $\lambda_3 = 1.4$, Pair 2: $\tau_4 = -0.5$, $\lambda_5 = 0.5$, and Pair 3: $\tau_3 = 0.5$, $\lambda_4 = 0.3$. The subscripts represent the targeted item of the five-item model (e.g. τ_5 refers to intercept parameter of the 5th item; λ_3 refers to the loading parameter of the 3rd item). The temporal position, in terms of the measurement occasion, of these non-invariant item parameter-pairs are described in the next few paragraphs.

The independent variables of this simulation study were sample size ($N = 50, 200,$ and 350) and measurement occasion ($T = 30,$ and 60) to simulate common research design of the ILM. Each of the non-invariant parameter-pairs were used at 10% of the overall measurement occasions for that particular parameter (see Table 3.1). For ex-

ample, τ_3 was generated to be non-invariant in 3 selected occasions of 30 total measurement occasion (Occasion 28 to 30; i.e., $\frac{3}{30} = 0.10 = 10\%$) or 6 selected occasions of 60 total measurement occasions (Occasion 55 to 60; i.e., $\frac{6}{60} = 0.10 = 10\%$). This is translated to 6% of the total number of intercept and loadings parameters are non-invariant (i.e., for 30 measurement occasions, 9 out of 150 intercept and loading parameters were non-invariant, respectively; for 60 measurement occasions, 18 out of 300 intercept and loading parameters were non-invariant, respectively).

To illustrate, in $T = 30$ condition, each pair was located at 3 selected consecutive occasions of the 30 measurement occasions: Pair 1 was located at Occasion 22 to 24, Pair 2 was located at Occasion 25 to 27, and Pair 3 was located at Occasion 28 to 30. In $T = 60$ condition, each pair was located at 6 of the 60 measurement occasions: Pair 1 was located at Occasion 43 to 48, Pair 2 was located at Occasion 49 to 54, and Pair 3 was located at Occasion 55 to 60 (see Table 3.1).

Table 3.1: Item Parameters

Measurement Occasions	τ_1	τ_2	τ_3	τ_4	τ_5	λ_1	λ_2	λ_3	λ_4	λ_5
01 ~ 21 (01 ~ 42)	0.00	0.00	0.00	0.00	0.00	1.00	1.00	1.00	1.00	1.00
22 ~ 24 (43 ~ 48)	0.00	0.00	0.00	0.00	<u>0.50</u>	1.00	1.00	<u>1.40</u>	1.00	1.00
25 ~ 27 (49 ~ 54)	0.00	0.00	0.00	<u>-0.50</u>	0.00	1.00	1.00	1.00	1.00	<u>0.30</u>
28 ~ 30 (55 ~ 60)	0.00	0.00	<u>0.50</u>	0.00	0.00	1.00	1.00	1.00	<u>0.50</u>	1.00

Note: The values in the table represent the thresholds (τ) and loadings (λ) parameter population value for each item at the specific temporal position of measurement occasions.

To investigate the impact of the presence of auto-regressive relationship between the latent factor which is commonly expected to be observed for repeated measures, a first-order autoregressive [AR(1)] factor covariance structure was simulated ($\rho = 0, 0.35,$ and 0.70). For example, given t number of total measurement occasions, the AR(1) factor covariance structure in the particular simulation would be as followed:

$$\begin{pmatrix} 1 & \rho & \rho^2 & \dots & \rho^t \\ \rho & 1 & \rho & \dots & \rho^{t-1} \\ \rho^2 & \rho & 1 & \dots & \rho^{t-2} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \rho^t & \rho^{t-1} & \rho^{t-2} & \dots & 1 \end{pmatrix}$$

A complete-data condition was simulated (i.e., 1-form design) to contrast with the planned-missing data condition (i.e., 3-form design). Missing data counterparts were created from the complete data to simulate a 3-form planned-missing data design paired with the two assignment methods (i.e., varying vs. constant) of the 3 forms. The 3-form design was accomplished by assigning the first and second indicator as Set X, and each of the remaining three items belong to Set A, B, and C, respectively (see Table 3.2).

In essence, each of the resulting form only consisted of 3 items. This effectively created 40% of missing data at each measurement occasion for each individual (i.e. 2 items out of 5 items were planned-missing). See Table 3.3 and Table 3.4 for an illustration of the two assignment methods with an example of six individuals and 5 measurement occasions.

Table 3.2: 3-form Design

Items	Set X	Set A	Set B	Set C	Form 1	Form 2	Form 3
1	O	-	-	-	O	O	O
2	O	-	-	-	O	O	O
3	-	O	-	-	O	-	-
4	-	-	O	-	-	O	-
5	-	-	-	O	-	-	O

Note: O represents item being included in the Set or Form. Set X and Set A comprise Form 1, Set X and Set B comprises Form 2, and Set X and Set C comprises Form 3.

3.2.2 Mplus Specifications

The Alignment method and the cross-classified factor model (see Figure 2.3.3 for an example of the model with 3-items; the current study extended the model to a 5-item

Table 3.3: Example of 3-form Varying Assignment with 6 Individuals

Individual	Occasion 1	Occasion 2	Occasion 3	Occasion 4	Occasion 5	...
1	1	2	3	1	2	
2	2	3	1	2	3	
3	3	1	2	3	1	...
4	1	2	3	1	2	
5	2	3	1	2	3	
6	3	1	2	3	1	

Note: Numbers in the Occasion columns represent the form (either 1, 2, or 3). Each individual received a different form at subsequent measurement occasion.

Table 3.4: Example of 3-form Constant Assignment with 6 Individuals

Individual	Occasion 1	Occasion 2	Occasion 3	Occasion 4	Occasion 5	...
1	1	1	1	1	1	
2	2	2	2	2	2	
3	3	3	3	3	3	...
4	1	1	1	1	1	
5	2	2	2	2	2	
6	3	3	3	3	3	

Note: Numbers in the Occasion columns represent the form (either 1, 2, or 3). Each individual received the same different form at all measurement occasions.

model) was applied on the simulated data as described in the previous section. This study used the Free alignment optimisation as opposed to the Fixed alignment optimisation as suggested by Asparouhov and Muthén (2014) for the Alignment method. To identify the cross-classified factor model, the within-level factor mean and the factor variance was fixed at 0 and 1, respectively.

For both the alignment method and the cross-classified factor model, Bayesian method with Gibbs sampling and Mplus default non-informative priors were used to estimate the posterior distribution of the parameters. The resulting parameters were then subjected to an ad-hoc comparison algorithm to identify time-invariant and time-varying (non-invariant) parameters.

3.2.3 Cross-Classified Model Ad-hoc Comparison Algorithm

An ad-hoc comparison algorithm to identify invariant and non-invariant parameters for the cross-classified factor model was developed based on the algorithm im-

plemented in Mplus for the Alignment method. Similar to the Mplus algorithm, the objective of this ad-hoc algorithm is to construct an invariant parameter-set and a non-invariant parameter set. 100 plausible values were generated via multiple imputation based on the resulting posterior distribution of each parameter of interest (i.e., τ and λ).

To construct the initial invariant-set for τ and λ respectively, the 90% highest density interval (HDI) was computed based on the plausible values. Parameters which 90% HDIs overlap were placed under the same set (e.g., if the 90% HDI of the τ of the first and second measurement occasion overlap, these two parameters are placed under the same invariant-set). If more than one such initial invariant-set are constructed, the invariant-set with the largest number of membership (i.e., parameters) is chosen as the starting initial-set.

The average of the parameter (using the plausible values) in the invariant-set is calculated, and each parameter's 90% HDI is compared to an interval constructed using this average value ± 0.05 (hereby refer to as the average interval). For each parameter that are already in the invariant-set, if the parameter's 90% HDI does not overlap with this average interval, the parameter is removed from the invariant-set. In contrast, for parameters that are not in the invariant-set but whose 90% HDI overlaps with the average interval are included in the invariant set. This process is iterated until there is no more change of membership in the invariant-set and non-invariant set or until the process reaches the maximum iteration (see section C.3 for the implementation of this algorithm in R and a diagram illustration of the algorithm).

In summary, this study considered the following research design to simulate the data to investigate the application of the Alignment method and the cross-classified factor model in identifying longitudinal non-invariance of factor loading and intercept parameters: 2 measurement occasions ($T = 30$, and 60) x 3 sample sizes ($N = 50$, 200 , and 350) x 3 AR(1) latent factor covariance structures ($\rho = 0$, 0.35 , and 0.70) x 3 missing-data designs ($PMD = 1$ -form, 3 -form varying assignment, and 3 -form constant assignment). 500 replications were done for each combination of the levels of the independent variables described above using R for data generation (see section C.1) and Mplus

for model fitting for both Alignment method and the cross-classified factor model (see section C.2).

As with typical simulation studies with large number of replications, descriptive statistics were used in place of inferential statistics to summarise the results. Inferential statistics were not commonly used because of the large number of replications (analogous to large sample size) would result in small p -values regardless of the magnitude of the effect sizes.

3.3 Results

3.3.1 Convergence

Model convergence for each replications were assessed using the Proportional Scale Reduction (PSR) index for both the Alignment method and the cross-classified model using the default Mplus settings (see Appendix A for more information on PSR and Mplus default). All replications converged successfully based on PSR.

3.3.2 Identification of (Non)-Invariant Parameters

Accuracy of the identification of the time-invariant and time-varying (non-invariant) parameters were quantified by the following computation: the proportion of times the ad-hoc algorithm correctly identifies the item parameter at each measurement occasion (e.g., $\tau_{j=1,t=1}$, $\lambda_{j=1,t=10}$) as invariant or non-invariant (i.e., accuracy) was first aggregated over the 500 replications. The accuracy of each parameter was further summarised by averaging the value over the number of measurement occasion in which the parameter is simulated as invariant or non-invariant. For items that were generated as fully time-invariant, the accuracy value for each parameter represents the overall invariance accuracy. For items non-invariant parameters, invariance and non-invariance accuracy were computed separately. Accuracy ranges between 0 and 1. A higher value represents higher accuracy of the method in identifying the parameter as invariant or non-invariant, respectively. A value higher or equal to 0.90 was taken to be an indicator

of acceptable accuracy for this study.

Accuracy of Invariant Intercept Parameters

Both the Alignment method and the cross-classified factor model performed equally well on identifying the time-invariant intercept parameters across all sample sizes, factor AR(1) structures, planned-missing data design, and number of measurement occasions considered in the data generation procedure. As presented in Table 3.5 and Table 3.6, both methods had close to 100% accuracy (i.e., a value of 1) for all five items in identifying intercept parameters that were designed to be time-invariant at the population level.

Accuracy of Invariant Loading Parameters

Similar to the results on invariant intercept parameters, both the Alignment method and the cross-classified factor model had close to or higher than 90% accuracy in identifying the time-invariant loadings parameters for the five items as seen in Table 3.7 and Table 3.8 across all simulation conditions. However, it was noted that the accuracy may be slightly affected by the presence of the AR(1) structure of the factor correlation. This is evident when the accuracy rates were slightly lower for some of the parameters in the $\rho = 0.35$ and $\rho = 0.70$ conditions as compared to the $\rho = 0.00$ condition, especially at the $T = 30$ condition for both methods. At the $T = 60$ condition, the impact of the AR(1) structure on accuracy were somewhat diminished.

Accuracy of Non-Invariant Intercept Parameters

Unlike the invariant parameters, the accuracy of identifying non-invariant intercept parameters was affected by sample sizes for both the Alignment method and cross-classified factor model. As evident from both Table 3.9 and Table 3.10, the accuracy of identifying non-invariant intercept was lower than 50% for all items in the $N = 50$ condition. Furthermore, even at moderate sample sizes (e.g., $N = 200$), the accuracy rates were also slightly lower with the presence of missing data (both varying- and constant-

assignment method) as compared to the complete-data counterpart. However, the results suggested that with longer measurement occasions (e.g., $T = 60$), this effect of missing data at $N = 200$ would be diminished at the cross-classified factor model but not the Alignment method. Nevertheless, both methods perform equally well with a larger sample size (e.g., $N = 350$) regardless of the number of measurement occasions.

Accuracy of Non-Invariant Loading Parameters

Similar to the results on non-invariant loading parameters, the accuracy rate of both the Alignment method and the cross-classified factor model were low with small sample sizes ($N = 50$), especially for item 3 (which deviates from its invariant counterparts by a magnitude of 0.40 at the population level, see Table 3.1). Also similarly, the accuracy rates were also slightly lower with the presence of missing data (both varying and constant-assignment method) as compared to the complete-data counterparts. However, the effect of missing data appears diminished for both methods with a longer measurement occasions (e.g., $T = 60$).

The accuracy rates were also slightly lower for the item 5 parameters (which deviates from its invariant counterparts by a magnitude of 0.50 at the population level, see Table 3.1) in the $\rho = 0.35$ and $\rho = 0.70$ condition as compared to the $\rho = 0.00$ condition, especially at the $T = 30$ condition for both methods. At the $T = 60$ condition, the impact of the AR(1) structure was somewhat diminished, similar to the invariant loading accuracy. Nevertheless, regardless of the simulation conditions, the cross-classified factor model resulted in higher accuracy in identifying non-invariant loading parameters than the Alignment method.

Table 3.5: Intercept Invariance Accuracy Rate for 30 Measurement Occasions Condition

N	ρ	PMD	Alignment Method					Cross-Classified Model				
			Items					Items				
			1	2	3	4	5	1	2	3	4	5
50	0.00	1-Form	0.999	0.998	0.998	0.999	0.999	0.999	1.000	0.994	0.994	0.992
		3-Form Varying	0.999	0.999	0.998	0.999	0.999	1.000	0.999	0.994	0.997	0.993
		3-Form Constant	0.999	0.999	0.999	0.999	0.998	1.000	1.000	0.993	0.997	0.992
	0.35	1-Form	0.999	0.998	0.999	0.999	0.999	1.000	1.000	0.994	0.993	0.990
		3-Form Varying	0.999	0.999	0.999	0.999	0.999	1.000	0.999	0.993	0.996	0.991
		3-Form Constant	0.999	0.999	0.999	0.999	0.999	1.000	0.999	0.993	0.997	0.991
	0.70	1-Form	0.999	0.998	0.999	0.998	0.999	1.000	1.000	0.993	0.993	0.992
		3-Form Varying	0.999	0.999	0.999	0.999	0.999	1.000	1.000	0.992	0.995	0.992
		3-Form Constant	0.999	0.999	0.999	0.999	0.999	1.000	1.000	0.993	0.995	0.993
200	0.00	1-Form	0.997	0.997	0.997	0.998	0.998	1.000	1.000	0.989	0.988	0.990
		3-Form Varying	0.997	0.998	0.998	0.998	0.998	1.000	1.000	0.985	0.985	0.989
		3-Form Constant	0.997	0.997	0.998	0.998	0.998	1.000	1.000	0.986	0.987	0.988
	0.35	1-Form	0.997	0.997	0.997	0.998	0.998	1.000	1.000	0.988	0.989	0.990
		3-Form Varying	0.996	0.996	0.998	0.998	0.998	1.000	1.000	0.986	0.986	0.988
		3-Form Constant	0.997	0.996	0.999	0.999	0.998	1.000	1.000	0.987	0.985	0.987
	0.70	1-Form	0.997	0.997	0.997	0.998	0.997	1.000	1.000	0.988	0.990	0.988
		3-Form Varying	0.996	0.998	0.998	0.999	0.998	1.000	1.000	0.986	0.988	0.989
		3-Form Constant	0.997	0.997	0.998	0.998	0.998	1.000	1.000	0.986	0.988	0.988
350	0.00	1-Form	0.997	0.996	0.997	0.998	0.998	1.000	1.000	0.990	0.992	0.990
		3-Form Varying	0.998	0.997	0.998	0.998	0.998	1.000	1.000	0.989	0.987	0.987
		3-Form Constant	0.997	0.996	0.999	0.997	0.998	1.000	1.000	0.987	0.986	0.986
	0.35	1-Form	0.996	0.996	0.997	0.996	0.999	1.000	1.000	0.991	0.991	0.992
		3-Form Varying	0.996	0.996	0.998	0.997	0.999	1.000	1.000	0.986	0.987	0.987
		3-Form Constant	0.996	0.995	0.998	0.997	0.999	1.000	1.000	0.988	0.986	0.986
	0.70	1-Form	0.996	0.996	0.998	0.998	0.998	1.000	1.000	0.992	0.991	0.992
		3-Form Varying	0.995	0.997	0.998	0.997	0.998	1.000	1.000	0.987	0.988	0.987
		3-Form Constant	0.996	0.997	0.998	0.998	0.999	1.000	1.000	0.990	0.988	0.987

Note: N = sample size, ρ = Factor AR(1) structure, PMD = Planned-Missing Data Design.

Table 3.6: Intercept Invariance Accuracy Rate for 60 Measurement Occasions Condition

N	ρ	PMD	Alignment Method					Cross-Classified Model				
			Items					Items				
			1	2	3	4	5	1	2	3	4	5
50	0.00	1-Form	0.999	0.998	0.998	0.999	0.999	0.999	1.000	0.994	0.994	0.992
		3-Form Varying	0.999	0.999	0.998	0.999	0.999	1.000	0.999	0.994	0.997	0.993
		3-Form Constant	0.999	0.999	0.999	0.999	0.998	1.000	1.000	0.993	0.997	0.992
	0.35	1-Form	0.999	0.998	0.999	0.999	0.999	1.000	1.000	0.994	0.993	0.990
		3-Form Varying	0.999	0.999	0.999	0.999	0.999	1.000	0.999	0.993	0.996	0.991
		3-Form Constant	0.999	0.999	0.999	0.999	0.999	1.000	0.999	0.993	0.997	0.991
	0.70	1-Form	0.999	0.998	0.999	0.998	0.999	1.000	1.000	0.993	0.993	0.992
		3-Form Varying	0.999	0.999	0.999	0.999	0.999	1.000	1.000	0.992	0.995	0.992
		3-Form Constant	0.999	0.999	0.999	0.999	0.999	1.000	1.000	0.993	0.995	0.993
200	0.00	1-Form	0.997	0.997	0.997	0.998	0.998	1.000	1.000	0.989	0.988	0.990
		3-Form Varying	0.997	0.998	0.998	0.998	0.998	1.000	1.000	0.985	0.985	0.989
		3-Form Constant	0.997	0.997	0.998	0.998	0.998	1.000	1.000	0.986	0.987	0.988
	0.35	1-Form	0.997	0.997	0.997	0.998	0.998	1.000	1.000	0.988	0.989	0.990
		3-Form Varying	0.996	0.996	0.998	0.998	0.998	1.000	1.000	0.986	0.986	0.988
		3-Form Constant	0.997	0.996	0.999	0.999	0.998	1.000	1.000	0.987	0.985	0.987
	0.70	1-Form	0.997	0.997	0.997	0.998	0.997	1.000	1.000	0.988	0.990	0.988
		3-Form Varying	0.996	0.998	0.998	0.999	0.998	1.000	1.000	0.986	0.988	0.989
		3-Form Constant	0.997	0.997	0.998	0.998	0.998	1.000	1.000	0.986	0.988	0.988
350	0.00	1-Form	0.997	0.996	0.997	0.998	0.998	1.000	1.000	0.990	0.992	0.990
		3-Form Varying	0.998	0.997	0.998	0.998	0.998	1.000	1.000	0.989	0.987	0.987
		3-Form Constant	0.997	0.996	0.999	0.997	0.998	1.000	1.000	0.987	0.986	0.986
	0.35	1-Form	0.996	0.996	0.997	0.996	0.999	1.000	1.000	0.991	0.991	0.992
		3-Form Varying	0.996	0.996	0.998	0.997	0.999	1.000	1.000	0.986	0.987	0.987
		3-Form Constant	0.996	0.995	0.998	0.997	0.999	1.000	1.000	0.988	0.986	0.986
	0.70	1-Form	0.996	0.996	0.998	0.998	0.998	1.000	1.000	0.992	0.991	0.992
		3-Form Varying	0.995	0.997	0.998	0.997	0.998	1.000	1.000	0.987	0.988	0.987
		3-Form Constant	0.996	0.997	0.998	0.998	0.999	1.000	1.000	0.990	0.988	0.987

Note: N = sample size, ρ = Factor AR(1) structure, PMD = Planned-Missing Data Design.

Table 3.7: Loading Invariance Accuracy Rate for 30 Measurement Occasions Condition

N	ρ	PMD	Alignment Method					Cross-Classified Model				
			Items					Items				
			1	2	3	4	5	1	2	3	4	5
50	0.00	1-Form	0.998	0.998	0.999	0.998	0.961	1.000	0.999	0.997	0.979	0.945
		3-Form Varying	0.999	0.999	0.999	0.999	0.972	0.999	0.999	0.996	0.985	0.945
		3-Form Constant	0.999	0.999	0.999	0.999	0.973	0.999	0.999	0.995	0.987	0.947
	0.35	1-Form	0.996	0.999	0.998	0.995	0.998	0.999	0.996	0.991	0.952	0.992
		3-Form Varying	0.998	0.999	0.999	0.998	0.999	0.997	0.996	0.992	0.966	0.987
		3-Form Constant	0.998	0.999	0.999	0.998	0.999	0.997	0.995	0.990	0.968	0.988
	0.70	1-Form	0.998	0.997	0.991	0.999	0.998	1.000	0.996	0.988	0.963	0.989
		3-Form Varying	0.999	0.999	0.996	0.999	0.999	0.999	0.996	0.988	0.973	0.988
		3-Form Constant	0.999	0.999	0.997	0.999	0.999	0.999	0.996	0.989	0.976	0.987
200	0.00	1-Form	0.998	0.998	0.998	0.998	0.961	1.000	1.000	0.992	0.980	0.943
		3-Form Varying	0.998	0.998	0.999	0.998	0.962	1.000	1.000	0.992	0.973	0.940
		3-Form Constant	0.998	0.998	0.998	0.998	0.961	1.000	1.000	0.991	0.971	0.938
	0.35	1-Form	0.963	0.997	0.985	0.966	0.994	0.989	0.985	0.934	0.941	0.965
		3-Form Varying	0.974	0.997	0.993	0.979	0.995	0.990	0.985	0.954	0.920	0.967
		3-Form Constant	0.973	0.998	0.991	0.979	0.997	0.990	0.986	0.949	0.920	0.973
	0.70	1-Form	0.979	0.967	0.958	0.996	0.989	0.992	0.987	0.934	0.965	0.947
		3-Form Varying	0.984	0.978	0.964	0.996	0.994	0.997	0.995	0.937	0.963	0.953
		3-Form Constant	0.984	0.977	0.963	0.997	0.994	0.997	0.995	0.942	0.962	0.957
350	0.00	1-Form	0.997	0.997	0.998	0.997	0.960	1.000	1.000	0.994	0.984	0.949
		3-Form Varying	0.997	0.997	0.998	0.997	0.960	1.000	1.000	0.991	0.981	0.938
		3-Form Constant	0.997	0.997	0.998	0.997	0.960	1.000	1.000	0.991	0.981	0.940
	0.35	1-Form	0.950	0.994	0.974	0.959	0.991	0.958	0.950	0.887	0.925	0.953
		3-Form Varying	0.958	0.996	0.982	0.965	0.995	0.963	0.945	0.892	0.938	0.957
		3-Form Constant	0.956	0.995	0.983	0.965	0.995	0.961	0.944	0.901	0.932	0.959
	0.70	1-Form	0.964	0.948	0.944	0.992	0.978	0.985	0.978	0.913	0.970	0.930
		3-Form Varying	0.971	0.959	0.953	0.995	0.987	0.991	0.974	0.912	0.961	0.937
		3-Form Constant	0.971	0.960	0.952	0.995	0.987	0.991	0.974	0.917	0.960	0.939

Note: N = sample size, ρ = Factor AR(1) structure, PMD = Planned-Missing Data Design. Values lower than the threshold of 0.900 are in bold.

Table 3.8: Loading Invariance Accuracy Rate for 60 Measurement Occasions Condition

N	ρ	PMD	Alignment Method					Cross-Classified Model				
			Items					Items				
			1	2	3	4	5	1	2	3	4	5
50	0.00	1-Form	0.999	0.999	0.999	0.998	0.980	1.000	1.000	0.999	0.982	0.969
		3-Form Varying	0.999	0.999	0.999	0.999	0.984	1.000	1.000	0.997	0.986	0.974
		3-Form Constant	0.999	0.999	0.999	0.998	0.984	1.000	1.000	0.997	0.985	0.976
	0.35	1-Form	0.997	0.999	0.999	0.997	0.997	0.999	1.000	0.998	0.976	0.991
		3-Form Varying	0.998	0.999	0.999	0.999	0.998	1.000	1.000	0.996	0.982	0.992
		3-Form Constant	0.998	0.999	0.999	0.998	0.999	1.000	1.000	0.996	0.982	0.994
	0.70	1-Form	0.998	0.999	0.999	0.999	0.996	0.999	1.000	0.998	0.973	0.990
		3-Form Varying	0.999	0.999	0.999	0.999	0.998	1.000	1.000	0.998	0.992	0.997
		3-Form Constant	0.999	0.999	0.999	0.999	0.998	1.000	1.000	0.999	0.993	0.998
200	0.00	1-Form	0.998	0.998	0.998	0.997	0.978	1.000	1.000	0.994	0.981	0.963
		3-Form Varying	0.998	0.998	0.998	0.998	0.979	1.000	1.000	0.993	0.971	0.959
		3-Form Constant	0.998	0.997	0.998	0.998	0.979	1.000	1.000	0.994	0.972	0.961
	0.35	1-Form	0.984	0.997	0.995	0.991	0.988	0.998	0.999	0.983	0.965	0.968
		3-Form Varying	0.988	0.997	0.996	0.995	0.993	0.999	0.999	0.984	0.963	0.974
		3-Form Constant	0.988	0.998	0.997	0.994	0.993	0.999	0.999	0.985	0.962	0.974
	0.70	1-Form	0.993	0.995	0.996	0.998	0.974	0.998	0.999	0.983	0.974	0.958
		3-Form Varying	0.994	0.996	0.997	0.998	0.982	1.000	0.998	0.988	0.968	0.968
		3-Form Constant	0.994	0.997	0.997	0.998	0.982	0.999	0.997	0.988	0.967	0.967
350	0.00	1-Form	0.997	0.997	0.998	0.997	0.979	1.000	1.000	0.992	0.986	0.969
		3-Form Varying	0.997	0.998	0.998	0.998	0.979	1.000	1.000	0.991	0.978	0.963
		3-Form Constant	0.997	0.997	0.998	0.998	0.979	1.000	1.000	0.992	0.979	0.962
	0.35	1-Form	0.978	0.994	0.993	0.984	0.979	0.999	0.998	0.960	0.966	0.960
		3-Form Varying	0.980	0.996	0.996	0.991	0.987	0.999	0.998	0.977	0.962	0.966
		3-Form Constant	0.980	0.995	0.996	0.990	0.986	0.999	0.998	0.978	0.963	0.964
	0.70	1-Form	0.987	0.992	0.991	0.997	0.961	0.998	0.995	0.966	0.981	0.948
		3-Form Varying	0.988	0.992	0.995	0.997	0.972	0.999	0.997	0.981	0.972	0.950
		3-Form Constant	0.989	0.993	0.996	0.997	0.973	0.999	0.997	0.980	0.973	0.949

Note: N = sample size, ρ = Factor AR(1) structure, PMD = Planned-Missing Data Design.

Table 3.9: Intercept Non-Invariance Accuracy Rate for 30 Measurement Occasions Condition

N	ρ	PMD	Alignment Method			Cross-Classified Model		
			Items			Items		
			3	4	5	3	4	5
50	0.00	1-Form	0.277	0.203	0.203	0.388	0.379	0.465
		3-Form Varying	0.121	0.067	0.067	0.362	0.109	0.166
		3-Form Constant	0.109	0.079	0.079	0.304	0.119	0.160
	0.35	1-Form	0.246	0.221	0.328	0.393	0.327	0.453
		3-Form Varying	0.105	0.084	0.110	0.340	0.132	0.176
		3-Form Constant	0.083	0.090	0.100	0.319	0.126	0.173
	0.70	1-Form	0.354	0.216	0.216	0.471	0.365	0.433
		3-Form Varying	0.180	0.082	0.082	0.451	0.193	0.175
		3-Form Constant	0.157	0.086	0.086	0.385	0.200	0.164
200	0.00	1-Form	0.997	0.995	0.995	0.997	0.998	0.997
		3-Form Varying	0.954	0.921	0.921	0.935	0.941	0.978
		3-Form Constant	0.957	0.932	0.932	0.903	0.938	0.977
	0.35	1-Form	0.998	0.987	0.999	0.997	0.996	0.997
		3-Form Varying	0.933	0.899	0.961	0.929	0.934	0.973
		3-Form Constant	0.931	0.900	0.961	0.895	0.933	0.981
	0.70	1-Form	0.999	0.995	0.995	0.997	0.998	0.995
		3-Form Varying	0.960	0.926	0.926	0.949	0.951	0.971
		3-Form Constant	0.963	0.933	0.933	0.938	0.951	0.970
350	0.00	1-Form	1.000	1.000	1.000	1.000	1.000	1.000
		3-Form Varying	0.999	0.999	0.999	0.999	0.999	1.000
		3-Form Constant	0.999	0.999	0.999	0.999	1.000	1.000
	0.35	1-Form	1.000	0.999	1.000	1.000	1.000	1.000
		3-Form Varying	0.999	0.998	1.000	1.000	0.999	1.000
		3-Form Constant	0.999	0.992	0.999	0.999	0.999	0.999
	0.70	1-Form	1.000	1.000	1.000	1.000	1.000	1.000
		3-Form Varying	0.999	1.000	1.000	0.999	0.998	0.999
		3-Form Constant	1.000	0.999	0.999	1.000	0.998	0.999

Note: N = sample size, ρ = Factor AR(1) structure, PMD = Planned-Missing Data Design. Item 1 and 2 were generated as fully invariant, therefore they were not included in this table. Values lower than the threshold of 0.900 are in bold.

Table 3.10: Intercept Non-Invariance Accuracy Rate for 60 Measurement Occasions Condition

N	ρ	PMD	Alignment Method			Cross-Classified Model		
			Items			Items		
			3	4	5	3	4	5
50	0.00	1-Form	0.290	0.228	0.311	0.436	0.288	0.324
		3-Form Varying	0.095	0.084	0.127	0.187	0.158	0.240
		3-Form Constant	0.100	0.088	0.120	0.148	0.165	0.208
	0.35	1-Form	0.254	0.238	0.291	0.389	0.267	0.304
		3-Form Varying	0.088	0.088	0.112	0.166	0.132	0.209
		3-Form Constant	0.087	0.084	0.125	0.126	0.135	0.166
	0.70	1-Form	0.264	0.262	0.306	0.399	0.330	0.337
		3-Form Varying	0.089	0.090	0.116	0.050	0.057	0.076
		3-Form Constant	0.092	0.088	0.122	0.037	0.042	0.063
200	0.00	1-Form	0.995	0.994	0.999	0.999	0.999	1.000
		3-Form Varying	0.948	0.924	0.968	0.987	0.976	0.988
		3-Form Constant	0.939	0.928	0.966	0.989	0.984	0.989
	0.35	1-Form	0.995	0.995	0.999	0.999	0.998	0.999
		3-Form Varying	0.939	0.928	0.968	0.985	0.975	0.988
		3-Form Constant	0.931	0.927	0.962	0.987	0.983	0.983
	0.70	1-Form	0.996	0.995	0.999	0.999	0.999	0.998
		3-Form Varying	0.932	0.936	0.964	0.985	0.976	0.987
		3-Form Constant	0.926	0.940	0.964	0.988	0.981	0.988
350	0.00	1-Form	1.000	1.000	1.000	1.000	1.000	1.000
		3-Form Varying	0.999	1.000	1.000	1.000	1.000	1.000
		3-Form Constant	0.998	0.999	0.999	1.000	1.000	1.000
	0.35	1-Form	1.000	1.000	1.000	1.000	1.000	1.000
		3-Form Varying	0.999	0.999	1.000	1.000	1.000	1.000
		3-Form Constant	0.999	0.999	0.999	1.000	1.000	1.000
	0.70	1-Form	1.000	1.000	1.000	1.000	1.000	1.000
		3-Form Varying	0.999	0.998	1.000	1.000	1.000	1.000
		3-Form Constant	0.999	0.999	0.999	1.000	1.000	1.000

Note: N = sample size, ρ = Factor AR(1) structure, PMD = Planned-Missing Data Design. Item 1 and 2 were generated as fully invariant, therefore they were not included in this table. Values lower than the threshold of 0.900 are in bold.

Table 3.11: Loading Non-Invariance Accuracy Rate for 30 Measurement Occasions Condition

N	ρ	PMD	Alignment Method			Cross-Classified Model		
			Items			Items		
			3	4	5	3	4	5
50	0.00	1-Form	0.057	0.618	0.210	0.097	0.917	0.469
		3-Form Varying	0.018	0.325	0.073	0.103	0.562	0.408
		3-Form Constant	0.018	0.341	0.059	0.091	0.515	0.433
	0.35	1-Form	0.067	0.788	0.181	0.145	0.989	0.121
		3-Form Varying	0.014	0.543	0.077	0.139	0.863	0.134
		3-Form Constant	0.014	0.553	0.076	0.114	0.834	0.139
	0.70	1-Form	0.067	0.883	0.121	0.169	0.995	0.196
		3-Form Varying	0.031	0.667	0.049	0.171	0.899	0.212
		3-Form Constant	0.023	0.654	0.043	0.151	0.871	0.222
200	0.00	1-Form	0.771	1.000	0.975	0.841	1.000	0.999
		3-Form Varying	0.377	0.998	0.805	0.530	0.999	0.984
		3-Form Constant	0.373	0.998	0.807	0.544	0.999	0.981
	0.35	1-Form	0.799	1.000	0.471	0.924	1.000	0.860
		3-Form Varying	0.394	0.992	0.399	0.675	1.000	0.673
		3-Form Constant	0.396	0.990	0.389	0.701	1.000	0.668
	0.70	1-Form	0.827	1.000	0.871	0.939	1.000	0.991
		3-Form Varying	0.443	0.999	0.607	0.743	1.000	0.916
		3-Form Constant	0.403	0.999	0.603	0.754	1.000	0.917
350	0.00	1-Form	0.988	1.000	1.000	0.991	1.000	1.000
		3-Form Varying	0.818	1.000	0.987	0.929	1.000	0.999
		3-Form Constant	0.805	1.000	0.987	0.939	1.000	1.000
	0.35	1-Form	0.986	1.000	0.670	0.992	1.000	0.975
		3-Form Varying	0.829	1.000	0.508	0.969	1.000	0.909
		3-Form Constant	0.821	1.000	0.505	0.969	1.000	0.903
	0.70	1-Form	0.987	1.000	0.993	0.996	1.000	1.000
		3-Form Varying	0.867	1.000	0.917	0.982	1.000	0.985
		3-Form Constant	0.843	1.000	0.909	0.976	1.000	0.991

Note: N = sample size, ρ = Factor AR(1) structure, PMD = Planned-Missing Data Design. Item 1 and 2 were generated as fully invariant, therefore they were not included in this table. Values lower than the threshold of 0.900 are in bold.

Table 3.12: Loading Non-Invariance Accuracy Rate for 60 Measurement Occasions Condition

N	ρ	PMD	Alignment Method			Cross-Classified Model		
			Items			Items		
			3	4	5	3	4	5
50	0.00	1-Form	0.072	0.630	0.208	0.087	0.849	0.488
		3-Form Varying	0.022	0.287	0.069	0.080	0.580	0.242
		3-Form Constant	0.020	0.294	0.070	0.082	0.591	0.235
	0.35	1-Form	0.070	0.681	0.217	0.096	0.906	0.308
		3-Form Varying	0.016	0.342	0.082	0.078	0.615	0.150
		3-Form Constant	0.020	0.356	0.084	0.080	0.584	0.138
	0.70	1-Form	0.066	0.777	0.216	0.117	0.955	0.350
		3-Form Varying	0.016	0.488	0.078	0.031	0.276	0.063
		3-Form Constant	0.019	0.495	0.071	0.030	0.231	0.053
200	0.00	1-Form	0.778	1.000	0.983	0.886	1.000	1.000
		3-Form Varying	0.366	0.995	0.811	0.672	1.000	0.986
		3-Form Constant	0.371	0.996	0.818	0.640	1.000	0.986
	0.35	1-Form	0.758	1.000	0.850	0.889	1.000	0.991
		3-Form Varying	0.365	0.998	0.663	0.699	1.000	0.914
		3-Form Constant	0.365	0.997	0.667	0.672	1.000	0.923
	0.70	1-Form	0.768	1.000	0.966	0.884	1.000	0.997
		3-Form Varying	0.364	0.998	0.791	0.667	1.000	0.973
		3-Form Constant	0.369	0.997	0.801	0.644	1.000	0.978
350	0.00	1-Form	0.987	1.000	1.000	0.997	1.000	1.000
		3-Form Varying	0.795	1.000	0.991	0.961	1.000	1.000
		3-Form Constant	0.777	1.000	0.989	0.947	1.000	0.999
	0.35	1-Form	0.986	1.000	0.970	0.997	1.000	0.998
		3-Form Varying	0.794	1.000	0.881	0.962	1.000	0.988
		3-Form Constant	0.789	1.000	0.888	0.951	1.000	0.988
	0.70	1-Form	0.987	1.000	0.999	0.996	1.000	1.000
		3-Form Varying	0.787	1.000	0.980	0.940	1.000	1.000
		3-Form Constant	0.787	1.000	0.984	0.941	1.000	0.999

Note: N = sample size, ρ = Factor AR(1) structure, PMD = Planned-Missing Data Design. Item 1 and 2 were generated as fully invariant, therefore they were not included in this table. Values lower than the threshold of 0.900 are in bold.

3.4 Summary and Discussion

This study aimed to compare the application of the Alignment method and the cross-classified factor model on the intensive longitudinal data under different simulation conditions of sample sizes, factor correlation AR(1) structure, planned-missing data, and measurement occasions in their ability to identify invariant and non-invariant measurement model parameters.

The results suggested that both methods generally perform equally well in identifying invariant and non-invariant intercept parameters under all simulation conditions except for the small sample size condition. Small sample size could have resulted in the lack of precision in the parameter estimates for the methods to detect the non-invariant parameters (which is defined as a parameter value that differs from the invariant parameters). The presence of missing-data (regardless of the assignment method) decreased the accuracy in identifying the invariant and non-invariant parameters slightly for both methods but it may be countered by a larger sample size (e.g., $N = 350$) for both methods. The impact of missing-data was also minimised in the cross-classified model with longer measurement occasions. This observation was perhaps due to the presence of more simulated non-invariant parameters in the longer measurement occasions condition for each parameter (i.e., 3 in the $T = 30$ condition and 6 in the $T = 60$ condition), which yielded a more precise estimation of the time-varying random effect in the cross-classified model, thereby leading to a higher accuracy.

The accuracy of the identification of invariant and non-invariant loading parameters were generally lower than that of intercept parameters. However, both methods generally perform equally well under all simulation conditions except for the small sample size condition and minor non-invariant condition (i.e. item 3 of which its non-invariant parameter was generated as $\lambda = 1.4$ as opposed to invariant parameter $\lambda = 1.0$). The presence of the AR(1) structure on the factor correlation, regardless of the magnitude, only decreased the accuracy on the loadings parameters but not the accuracy on intercepts parameters across both methods, but this effect was minimised with longer measurement occasions. The results also suggested that the Alignment method had a

generally higher accuracy in identifying invariant loading parameters more than the cross-classified model, while the cross-classified model had a generally higher accuracy in identifying non-invariant loading parameters than the Alignment method. This suggests that the Alignment method tends to under-identify the non-invariant loading parameters as compared to the cross-classified model; while the cross-classified model tends to under-identify the invariant loading parameters as compared to the Alignment method.

3.5 Limitations and Future Directions

The current study used the same ratio regardless of the total number of measurement occasions. Future research may benefit from manipulating the ratio of invariance to non-invariance parameter to investigate the effect of the proportion of non-invariance parameters on the identification of invariant/non-invariant parameters. I expect that the ratio to have an impact on the accuracy rate especially for the cross-classified factor model as the random effect of time (using the variance parameter) would be better estimated with an larger variability in the parameters.

On another note, the degree of deviations of the non-invariant parameter from the invariance parameter should also be systematically investigated for both the intercepts and loadings parameters. The study had shown preliminary indication that the degree of deviations in the non-invariant loadings parameter had an effect on the accuracy rate. Future research should also investigate if the effect would be observed in the intercepts parameters. The robustness of the identification of invariant or non-invariant intercepts against the degree of deviations has to be tested.

It is commonly for empirical research to use ordered-categorical rating scales (e.g., agreement scale) which are inherently on the ordinal scale of measurement. The results in this study may not be able to generalise to the case of categorical rating scales as the measurement models for categorical rating scales have additional thresholds parameters in place of the intercepts parameters. I expect the results on the factor loadings to

be similar, but additional studies on the measurement invariance for categorical rating data with threshold parameters has to be investigated.

3.6 Recommendations

Based on the results from this study, I would suggest researchers to apply the cross-classified model if possible to ensure a sufficient accuracy rate on identifying both invariant and non-invariant measurement model parameters. However, due to the complexity of the model, a larger sample sizes and longer measurement occasions is required for the post-hoc comparison algorithm to reliably identify the invariant and non-invariant parameter sets.

Planned-missing data can also be used if there is a sufficiently large sample size (e.g., $N > 200$) regardless of the assignment method. However, a varying-form assignment method may be more practical to avoid practice effects due to small interval between two measurement occasions (Jorgensen et al., 2014).

It is common to proceed with the modelling of relationships between variables (i.e., causal modelling) after the test of measurement invariance. However, the provision of a remedy after measurement non-invariance was detected in the IILM is out of the scope of this chapter. Nevertheless, drawing inferences from the traditional panel longitudinal data literature, the evidences suggested that non-invariance in measurement parameters should not be ignored and they should be appropriately modelled in the subsequent causal modelling to avoid bias in parameter estimates and inflation of error rate (e.g., Leite, 2007; Xu et al., 2020).

Chapter 4

Study 2

The Impact of Sample Size, Measurement Occasions, Effect Size, and Planned-Missingness on Parameter Estimates of Intensive Longitudinal Mediation Model

Study 1 investigated the use of the Alignment method and cross-classified factor model to identify invariant and non-invariant measurement parameters (i.e., intercepts and factor loadings) as a means to establish longitudinal measurement invariance in ILD. Once longitudinal measurement invariance has been established, the modelling of longitudinal differences and change can be proceeded (Meredith, 1964).

Psychological research are often interested in understanding the mechanism underlying phenomena and the conditions that facilitate or inhibit the relationships among variables. The mediation process has been one of the integral parts of behavioural research (Cole & Maxwell, 2003). Traditionally, the study of the mediation process has focused on using cross-sectional data (i.e., Baron & Kenny, 1986). However, in the past decade, there has been a shift towards the utility of longitudinal data for a more rigorous analysis and interpretation of causal relationship between variables (e.g., Cole & Maxwell, 2003; Maxwell & Cole, 2007).

The mediation process is also an interest in studies using the intensive longitudinal methodology. For example, Flueckiger et al. (2014) recently investigated the mediation

effect of positive and negative affect on the relationship between health behaviour and academic performance using data collected daily from 72 students for 32 days using the multilevel structural equation model.

Instead of the multilevel structural equation model, the current study focused the evaluation on the dynamic structural equation modelling (DSEM) framework that was recently developed in the field of social sciences (Asparouhov et al., 2018).

4.1 Background

To the author's knowledge, only one study has evaluated and provided recommendations for the application of planned-missing data (PMD) with a focus on matrix sampling design (implemented using multiple form design) in the context of intensive longitudinal research design (i.e., Silvia et al., 2014). Using multilevel structural equation model with level-1 latent outcome variable (measured by 4 items) as the statistical model of choice, Silvia et al. (2014) investigated the effect of types of PMD design of the 4 items (complete-data/single-form design vs. three-form design without anchor items vs. three-form design with anchor item), sample size (i.e., level-2 sample size: $N = 50, 100, 150,$ and 200), measurement occasion ($T = 15, 20, 40,$ and 60) on model convergence rate, and parameter and standard error (SE) bias for several selected parameters of interest. As with conventional estimation of a multilevel structural equation model, the full-information maximum likelihood (FIML) with robust standard error was used to estimate the parameters.

Silvia et al. (2014) concluded that the model convergence rate is not affected by PMD but only by sample size (minimum sample size should be 100 people with 30 measurement occasion in total). Even though parameter estimates have minimal bias regardless of the PMD type, the SE bias increased as a function of missing-ness, in that, for the level-1 parameters, complete-data design has the smallest SE bias, and the matrix sampling design has the largest SE bias. However, Silvia et al. (2014) found that as observations increased in both level-1 (measurement occasions) and level-2 (individ-

uals), the SE biases would decrease.

Silvia et al.'s (2014) study provided some indications that PMD did not introduce substantial parameter bias and that sample size may negate the impact of PMD on the standard error. However, the authors had only considered missing data on the indicators of the latent dependent variable in their design. In the application of the multiple-form design, missing data could be planned on both the indicators of level-1 *predictors* as well as on the *dependent variable*. With the new development of the methodology tailored for the intensive longitudinal data, it is also imperative to replicate the findings in the newly developed DSEM framework.

The DSEM was previously evaluated in Schultzberg and Muthén (2018) using a series of models with varying number of individual and measurement occasions in the simulation of intensive longitudinal data. Using an autoregressive multilevel model with observed variables (as opposed to latent variables) as a basis, a lag-1 relationship of a single variable was modelled on the level-1 while the corresponding random intercept and slope were modelled on level-2 as mediators in some model variations and as outcomes in other variations. Schultzberg and Muthén (2018) considered sample size of $N = 10, 15, 20, 25, 50, 100, \text{ and } 200$, and measurement occasions of $T = 10, 15, 20, 25, 50, 100, \text{ and } 200$. It was found that in general a larger sample size may be able to compensate for the inaccuracy in estimation brought by smaller number of measurement occasions (Schultzberg & Muthén, 2018). However, Schultzberg and Muthén (2018) also noted that this may also depend on the type of parameters (e.g., intercept, slope, fixed effects, random effects) of a specific model and the level where the parameters were located (i.e., level-1 or level-2), as well as the relationships between the variables (e.g., regression of random slope coefficient on level-2 covariates, regression of level-2 outcome on random slope coefficient, etc). Even though the authors have provided some recommendations on the analysis requirement for DSEM, their simulation study was primarily based on a complete-data scenario. Missing data was not considered except for one of the model variations.

4.2 Objectives

The objective of this study was therefore to expand on Schultzberg and Muthén’s (2018) evaluation on DSEM by investigating the effect of sample size, length of measurement occasion, effect size, and degree of planned-missing data on the parameter estimates of autoregressive multilevel mediation models with latent variables at both level-1 and level-2.

4.3 Method

4.3.1 Data-generating Mediation Models

The models considered in this simulation study were based on MacKinnon’s (2008) autoregressive mediation model I and Preacher et al. (2010) multilevel mediation model. More specifically, the current simulation study used the 1-1-1 and 2-1-1 mediation process model as described in Preacher et al. (2010) with autoregressive features described in MacKinnon (2008). The autoregressive structure was included to represent longitudinal relationship between variables, where variables in time t is affected by variables in the previous time point $t - 1$ (i.e., lag-1 relationship). 1-1-1 refers to the data collection design that predictor X , mediator M , and outcome Y are all measured at the level-1 (i.e., across time) of a multilevel nested structure; while a 2-1-1 refers to the design that predictor X is measured at level-2 (i.e., individual) and mediator M and outcome Y are measured at level-1 (i.e., across time).

Figure 4.3.1 and Figure 4.3.2 illustrate the two DSEM models used in the study following structural equation modelling notations and conventions reviewed in Ho et al. (2012). The parameters of interest in the simulation study are highlighted as a solid-lined arrow (as opposed to a dotted-line arrow). Referring to Figure 4.3.1, the model is essentially a 2-level latent autoregressive lag-1 model.

As with a DSEM multilevel model, each observed variable collected from individual i at each time t (e.g. $X_{1,it}$) is statistically decomposed into two independent *latent*

components: the within-individual (i.e., state) component and the between-individual (i.e., trait) component with the assumption that the variability in the particular variable can be attributed to both longitudinal time t and individual i :

$$Y_{it} = Y_{it}^W + Y_i^B \quad (4.1)$$

where $Y_{it}^W \sim N(0, \sigma_{Y^W}^2), Y_i^B \sim N(\mu_Y, \sigma_{Y^B}^2)$

Equation 4.1 uses the Y variable as an example and is generalisable to all variables that are measured at each time t in this simulation, that is, variables X_j, M_j , and Y_j in the 1-1-1 model but only variables M_j , and Y_j in the 2-1-1 model because variable X in this model is simulated to only vary across individual but time-invariant. The superscript W and B represent the within-level and the between-level of the hierarchical nested structure of the data respectively. This is illustrated in the left-panel of Figure 4.3.1 and Figure 4.3.2.

It should be noted that DSEM employs the latent mean centering approach on the decomposition to avoid the Ludtke's bias on contextual effect (Asparouhov & Muthén, 2020) and Nickell's bias on autoregression parameters (Asparouhov et al., 2018) in which the within component is latent mean centered.

These two components were further defined as part of the within-level and between-level measurement models to specify the latent variables using the standard common factor model representation (using variable Y as an example and is applicable to all variables that are measured at each time t in this simulation):

$$Y_{j-it}^W = \lambda_j^W \eta_{Y_{it}}^W + \epsilon_{j-it}^W \quad (4.2)$$

$$Y_{j-i}^B = \nu_j^B + \lambda_j^B \eta_{Y_i}^B + \epsilon_{j-i}^B$$

Values for the measurement model parameters used for data generation were as the following for all items and factors:

- $\lambda_j^W = 0.70, \eta^W \sim N(0, \sigma_{\eta^W}^2 = 1),$ and $\epsilon_{j-it}^W \sim N(0, \sigma_{\epsilon_{j-it}^W}^2 = 0.51),$
- $\lambda_j^B = 0.459, \eta^B \sim N(0, \sigma_{\eta^B}^2 = 1),$ and $\epsilon_{j-i}^B \sim N(0, \sigma_{\epsilon_{j-i}^B}^2 = 0.2193),$ and

- $v_j^B = 0$

The λ and σ_ε^2 population values at both levels were chosen to achieve an intra-class correlation (ICC) of approximately 0.30 for each indicator j using the definition of ICC (Hoffman, 2015):

$$ICC = \frac{\sigma^{B^2}}{\sigma^{B^2} + \sigma^{W^2}} = \frac{\lambda_j^{B^2} * \sigma_{\eta^{B^2}}^2 + \sigma_{\varepsilon_{j-i}^B}^2}{\lambda_j^{B^2} * \sigma_{\eta^{B^2}}^2 + \sigma_{\varepsilon_{j-i}^B}^2 + \lambda_j^{W^2} * \sigma_{\eta^{W^2}}^2 + \sigma_{\varepsilon_{j-it}^W}^2} \quad (4.3)$$

An ICC ranges from 0 to 1, with higher value representing higher heterogeneity in the between-level units and relative homogeneity in within-level units. An ICC of 0.30 indicates that 30% of the total variability of each item is due to between-individual differences (level-2 unit) and 70% due to time (level-1 unit).

1-1-1 Mediation Model

For the 1-1-1 data-generating mediation model as illustrated in Figure 4.3.1, the structural paths on both level-1 and level-2 were defined between the latent measurement factors using the common factor model as presented in Equation 4.2:

Within-level:

$$\begin{aligned} \eta_{X_{it}}^W &= \phi_X * \eta_{X_{it-1}}^W + \varepsilon_{X_{it}}^W \\ \eta_{M_{it}}^W &= \phi_M * \eta_{M_{it-1}}^W + \alpha^W * \eta_{X_{it-1}}^W + \varepsilon_{M_{it}}^W \\ \eta_{Y_{it}}^W &= \phi_Y * \eta_{Y_{it-1}}^W + \beta^W * \eta_{M_{it-1}}^W + \tau^W * \eta_{X_{it-1}}^W + \varepsilon_{M_{it}}^W \end{aligned} \quad (4.4)$$

where $\phi_X = \phi_M = \phi_Y = 0.2$, and

$$\sigma_{\varepsilon_X^W}^2 = \sigma_{\eta_X^W}^2 - \phi_X^2 * \sigma_{\eta_X^W}^2 = 1 - \phi_X^2,$$

$$\sigma_{\varepsilon_M^W}^2 = \sigma_{\eta_M^W}^2 - \phi_M^2 * \sigma_{\eta_M^W}^2 - \alpha^{W^2} * \sigma_{\eta_X^W}^2 = 1 - \phi_M^2 - \alpha^{W^2}, \text{ and}$$

$$\sigma_{\varepsilon_Y^W}^2 = \sigma_{\eta_Y^W}^2 - \phi_Y^2 * \sigma_{\eta_Y^W}^2 - \beta^{W^2} * \sigma_{\eta_M^W}^2 - \tau^{W^2} * \sigma_{\eta_X^W}^2 = 1 - \phi_Y^2 - \beta^{W^2} - \tau^{W^2}$$

Between-level:

$$\begin{aligned}
\eta_{M_i}^B &= \alpha^B * \eta_{X_i}^B + \varepsilon_{M_i}^B \\
\eta_{Y_i}^B &= \beta^B * \eta_{M_i}^B + \tau^B * \eta_{X_i}^B + \varepsilon_{Y_i}^B
\end{aligned} \tag{4.5}$$

where $\sigma_{\varepsilon_M^B}^2 = \sigma_{\eta_M^B}^2 - \alpha^{B^2} * \sigma_{\eta_X^B}^2 = 1 - \alpha^{B^2}$, and

$$\sigma_{\varepsilon_Y^B}^2 = \sigma_{\eta_Y^B}^2 - \beta^{B^2} * \sigma_{\eta_M^B}^2 - \tau^{B^2} * \sigma_{\eta_X^B}^2 = 1 - \beta^{B^2} - \tau^{B^2}$$

2-1-1 Mediation Model

As illustrated in Figure 4.3.2, the 2-1-1 data-generating mediation model differs from the 1-1-1 model in which X_i is a level-2 (time-invariant) observed variable and it is simulated as a binary variable to represent grouping variables (e.g., control-treatment group, male-female dichotomy, etc.). A standard normal distribution $N(0, 1)$ was used to generate the initial X_i^* and was dichotomised using a threshold of 0 after all data was generated, as such

$$X_i = \begin{cases} 0, & \text{if } X_i^* \leq 0 \\ 1, & \text{otherwise} \end{cases}$$

As with the 1-1-1 model, the structural paths on level-1 were defined among the latent measurement factor in the common factor model as presented in Equation 4.2, while the structural paths on level-2 were defined among the observed dichotomous X variable, and latent M and Y variables.

Within-level:

$$\begin{aligned}
\eta_{M_{it}}^W &= \phi_M * \eta_{M_{it-1}}^W + \varepsilon_{M_{it}}^W \\
\eta_{Y_{it}}^W &= \phi_Y * \eta_{Y_{it-1}}^W + \beta^W * \eta_{M_{it-1}}^W + \varepsilon_{M_{it}}^W
\end{aligned} \tag{4.6}$$

where $\phi_M = \phi_Y = 0.2$, and

$$\sigma_{\varepsilon_M^W}^2 = \sigma_{\eta_M^W}^2 - \phi_M^2 * \sigma_{\eta_M^W}^2 = 1 - \phi_M^2, \text{ and}$$

$$\sigma_{\varepsilon_Y^W}^2 = \sigma_{\eta_Y^W}^2 - \phi_Y^2 * \sigma_{\eta_Y^W}^2 - \beta^{W^2} * \sigma_{\eta_M^W}^2 = 1 - \phi_Y^2 - \beta^{W^2}$$

Between-level:

$$\begin{aligned}\eta_{M_i}^B &= \alpha^B * X_i + \varepsilon_{M_i}^B \\ \eta_{Y_i}^B &= \beta^B * \eta_{M_i}^B + \tau^B * X_i + \varepsilon_{Y_i}^B\end{aligned}\tag{4.7}$$

where $\sigma_{\varepsilon_M^B}^2 = \sigma_{\eta_M^B}^2 - \alpha^{B^2} * \sigma_X^2 = 1 - \alpha^{B^2}$, and

$$\sigma_{\varepsilon_Y^B}^2 = \sigma_{\eta_Y^B}^2 - \beta^{B^2} * \sigma_{\eta_M^B}^2 - \tau^{B^2} * \sigma_X^2 = 1 - \beta^{B^2} - \tau^{B^2}$$

4.3.2 Simulation Setup

To simulate data to represent real-world observations as close as possible, the sample sizes and measurement occasions considered in the current simulation were $N = 50, 100, 200,$ and $350,$ and $T = 30$ and $60,$ respectively. The population parameter values were chosen to represent a relative smaller and larger effect size $\beta = 0.3$ and $0.6,$ respectively, based on Krull and MacKinnon (2001).

Missing data was simulated using a 3-form design (see Study 1) with a varying-form distribution pattern. With reference to the 1-1-1 model (see Figure 4.3.1), each factor was measured by 5 items at each time point. Three levels of missing data percentages were considered: PMD = 0% (i.e. full data), 20% (i.e. 3 out of 15 items were omitted), and 40% (i.e. 6 out of 15 items were omitted). See Table 4.1 and Table 4.2 for the two corresponding 3-form designs. Similar operations were done on the 2-1-1 model (see Figure 4.3.2) with an exception of the X variable. In the 2-1-1 model, X was simulated as a level-2 time-invariant observed binary variable and was not simulated as being measured using items. Hence, PMD = 0% (i.e. full data), 20% (i.e. 2 out of 10 items measuring M and Y were omitted), and 40% (i.e. 4 out of 10 items measuring M and Y were omitted).

500 replications were done for each combination of the levels of the independent variables described above using both Mplus and R for data generation (see section D.1) and Mplus for model fitting (see section D.2). The PSR factor was used to evaluate the convergence of the two chains for each parameters after a minimum of 6000 iterations for the complete-data condition (8000 iterations for the missing-data conditions).

Table 4.1: 3-form Design with 20% Planned Missing

Forms	X1	X2	X3	X4	X5	M1	M2	M3	M4	M5	Y1	Y2	Y3	Y4	Y5
A	O	O	O	O	-	O	O	O	O	-	O	O	O	O	-
B	O	O	O	-	O	O	O	O	-	O	O	O	O	-	O
C	O	O	-	O	O	O	O	-	O	O	O	O	-	O	O

Note: The symbol O represents item being included in the Form. The columns represent 5 items from the respective X, M, and Y latent variables. This table represents the setup for the 1-1-1 mediation model. X1 to X5 were omitted from the 2-1-1 mediation model setup, and was replaced by a single binary variable. This table also represents the setup for the time-varying effect model in chapter 5.

Table 4.2: 3-form Design with 40% Planned Missing

Forms	X1	X2	X3	X4	X5	M1	M2	M3	M4	M5	Y1	Y2	Y3	Y4	Y5
A	O	O	O	-	-	O	O	O	-	-	O	O	O	-	-
B	O	O	-	O	-	O	O	-	O	-	O	O	-	O	-
C	O	O	-	-	O	O	O	-	-	O	O	O	-	-	O

Note: The symbol O represents item being included in the Form. The columns represent 5 items from the respective X, M, and Y latent variables. This table represents the setup for the 1-1-1 mediation model. X1 to X5 were omitted from the 2-1-1 mediation model setup, and was replaced by a single binary variable. This table also represents the setup for the time-varying effect model in chapter 5.

Fitted Model

The models that were used to fit the generated data were slightly different from the data-generating models in a few aspects (see Figure 4.3.1 and Figure 4.3.2). The structural disturbances on level-1 in the data-fitting model in Figure 4.3.3 and Figure 4.3.4 were modelled to covary as part of the default setting in Mplus. The intercept of the level-2 indicators latent-component were also estimated as per the multilevel CFA model in Equation 4.2 and as part of the default setting in Mplus.

4.3.3 Evaluation Measures

As the indirect effects of a mediation model is often a function the direct effects between variables, this study only focused on the direct effects, and not the computation of indirect effects. For *each* of the model parameters of interest (i.e. effects represented as solid lines in Figure 4.3.3 and Figure 4.3.4), three measures were calculated to evaluate the performance of the estimator under the experimental conditions: relative bias,

coverage, and rejection for each parameter of interest.

Relative Bias

Relative bias (RB) is defined as the difference between point-estimate ($\hat{\theta}$) and the true value (θ) of the parameter divided by the true value,

$$RB = \left(\frac{\hat{\theta} - \theta}{\theta} \right) \quad (4.8)$$

A positive value represents an over-estimation and a negative value represents an under-estimation, relative to the true value. For example, an RB value of 0.02 represents a 2% *over-estimation* relative to the true value; an RB value of -0.02 represents a 2% *under-estimation* relative to the true value. An *absolute* RB value of less than 5% indicates trivial bias, values between 5% and 10% indicate moderate bias, while values greater than 10% indicate substantial bias (e.g., Flora & Curran, 2004). The median of the posterior distribution was used as the point estimate as per default in Mplus. Readers who are not familiar with the concept of the parameter posterior distribution may refer to Appendix A.

Coverage

Coverage is defined as the average number of replications with the highest density interval (HDI) containing the true population parameter value,

$$Coverage = \frac{\text{number of HDI that contains } \theta}{\text{number of replications}} \quad (4.9)$$

Coverage ranges from 0 to 1, with 0 representing none of the HDIs across the replications contain the true value, and a value of 1 represents all HDIs across to the replications contain the true value. The 90% HDI was used for the computation as recommended by Kruschke (2014). For the purpose of this study, a coverage value of 0.87 and above is considered good coverage, adapting the criteria used in Schultzberg and Muthén (2018). Readers who are not familiar with the concept of HDI may refer to

Appendix A.

Rejection

Rejection is defined as the average number of replications with HDI that does not contain the Region of Practical Equivalence (ROPE; see Appendix A for more details),

$$Rejection = \frac{\text{number of HDI that do not contain ROPE}}{\text{number of replications}} \quad (4.10)$$

The ROPE for the standardized parameters of interest for this study was specified as $[-0.05, 0.05]$, as suggested in Kruschke (2018). Rejection ranges from 0 to 1, with 0 representing all of the 90% HDIs across the replications contained the ROPE, and a value of 1 represents none of the 90% HDIs across the replications contained the ROPE. A value of 0.80 and above (a value commonly used in the NHST context) is considered an acceptable rejection for the purpose of this study.

Convergence

Convergence of the Gibbs Sampling MCMC for parameters in each replication was assessed using the Potential Scale Reduction (PSR) factor. Only replications that successfully converged were included in the analysis, and replications that failed to converge were not replaced with new replications. Readers who are not familiar with the PSR factor may refer to Appendix A.

4.4 Results

The evaluation measures were reported for the 1-1-1 and 2-1-1 models separately in the following section.

4.4.1 1-1-1 Mediation Model

Convergence Rate

The convergence rate approached 1 (i.e., all replications converged successfully) as the sample size (N) increased from 25 to 350. The convergence rate was at least 90% at $N = 100$, and reached 100% at $N = 200$. The results suggested that the convergence rate was only dependent on the sample with no clear patterns in other factors considered in the design (i.e. measurement occasions T , effect size ES , and planned-missing data rate PMD), as evident by the convergence rate in Table 4.3.

Table 4.3: 1-1-1 Mediation Model Convergence Rate for 500 Replications

T	ES	PMD	N				
			25	50	100	200	350
30	0.3	0%	0.78	0.73	0.95	1.00	1.00
		20%	0.89	0.76	0.95	1.00	1.00
		40%	0.74	0.72	0.89	1.00	1.00
	0.6	0%	0.89	0.65	0.96	1.00	1.00
		20%	0.90	0.68	0.96	1.00	1.00
		40%	0.92	0.66	0.91	1.00	1.00
60	0.3	0%	0.87	0.72	0.90	1.00	1.00
		20%	0.75	0.73	0.91	1.00	1.00
		40%	0.81	0.72	0.94	1.00	1.00
	0.6	0%	0.80	0.65	0.95	1.00	1.00
		20%	0.75	0.71	0.95	1.00	1.00
		40%	0.78	0.70	0.96	1.00	1.00

Note: N = Sample Size; T = measurement occasions; ES = Effect Size, PMD = Planned-Missing Data Percentage. The values represent the proportion of converged replications out of the 500 total replications for each combination of conditions (e.g., 1 = all 500 replications converged successfully; 0.80 = 400 out of 500 replications converged successfully).

Relative Bias

As observed in both Table 4.4 for the level-1 (between time) parameters and Table 4.4 for the level-2 (between person) parameters, the parameters were generally systematically under-estimated on average (i.e. the estimated parameters were smaller

than the population value) and the parameter relative bias was higher in the level-2 parameters compared to the level-1 parameters.

The degree of relative bias in the level-1 parameters (see Table 4.4) were largely affected by the parameters and the effect size (ES). The relative bias of the α^W (i.e., effect of lag-1 X on M) in each combination of experimental conditions were within the acceptable boundary of -0.05 and 0.05. Comparing the relative bias of β^W (i.e., effect of lag-1 M on Y) and τ^W (i.e., effect of lag-1 X on Y) with α^W , the parameter bias was generally larger for β^W and the largest for τ^W at each combination of the experimental factors (i.e. N , T , ES and N). On top of that, there seemed to be an effect of the ES with the larger effect size ($ES = 0.60$) generally having larger relative bias than smaller effect size ($ES = 0.030$).

Even though substantial impact of sample size (N) on the relative bias was not observed, within-conditions variability of the relative bias could be affected by N . The variability (quantified by the standard deviation presented within the brackets in Table 4.4) decreased as N increased from the left to the right columns across the three parameters of interest. This suggested that the point estimate of the parameters between the replications were more similar with a larger sample sizes, despite the fact that a systematic under-estimation had been observed for all conditions of sample sizes.

Furthermore, there was no substantial effect of the amount of missing data (PMD) on the relative bias. For each parameter at each combination of the experimental factors (i.e., T , ES and N), a comparison of the relative bias values of the $PMD = 20\%$ and 40% levels were highly similar to the relative bias at $PMD = 0\%$. There was also no obvious effect of measurement occasions (T) on relative bias. For each parameter at each combination of the experimental factors (i.e., ES , PMD , and N), a comparison of the relative bias values of $T = 30$ were similar to the relative bias at $T = 60$.

Similar to the results on the level-1 parameters, the magnitude of relative bias in the level-2 parameters (see Table 4.5) was not greatly affected by the amount of missing data (PMD) and measurement occasions (T ; however, the pattern of T was mixed in the lower N conditions. In contrast, at higher N , there was no difference between $T =$

30 and $T = 60$ at each combination of experimental factors). In contrast to the level-1 parameters, the level-2 relative bias was also not only effected by the parameter and the effect size (ES), but also the sample size (N).

Comparing the relative bias of β^B (i.e. effect of M on Y) and τ^B (i.e. effect of X on Y) with α^B (i.e., effect of X on M), it was clear that the parameter relative bias was generally larger for β^B and the largest for τ^B at each combination of the experimental factors (i.e., N , T , ES and N). On top of that, the relative bias was generally out of the acceptable boundary of -0.05 and 0.05 at the small sample size conditions ($N = 25, 50$, and 100) in most combinations of the experimental factors. At large sample size ($N = 200$ and 350), the pattern of the effect of ES was clearer and similar to that of the level-1 parameters, in that conditions with larger effect size ($ES = 0.60$) showed a larger relative bias generally comparing to smaller effect size ($ES = 0.30$).

Coverage

Comparing the coverage of the level-1 (between time) parameters and the level-2 (between person) parameters, the level-2 parameters showed better coverage than the level-1 parameters (see Table 4.6 and Table 4.7). For an instance, the coverage value for some level-1 parameters (i.e. β^W and τ^W at the $N = 350$ and $ES = 0.60$ condition combination) was 0%. A value of 0 represents that none of the 90% HDI of the parameter of interest contained the true value across the successful replications for that combination of simulation conditions.

While the results did not indicate substantial difference in the coverage at different levels of measurement occasions (T) and planned-missing data (PMD), the effect of sample size (N) and effect size (ES) was observed on both level-1 and level-2 parameters, with both showing similar trends in coverage. The coverage generally decreased with an increase of sample size from $N = 25$ to $N = 350$ for all parameters of interest regardless of combination of other experimental factors (i.e., T , ES , and PMD). In addition, the coverage of the parameters at $ES = 0.60$ was generally lower than those at the $ES = 0.30$ conditions.

Rejection

An inspection of Table 4.8 showed that the rejection values for all level-1 parameters under all combinations of simulation conditions of sample size (N), measurement occasion (T), effect size (ES), and planned-missing data (PMD) were 1 (i.e., 100%), indicating that all the 90% HDIs of the parameters across the replications did not contain the region of practical equivalence (ROPE). In this particular case, there was no effect of the experimental factors on the parameter rejection.

In contrast, an effect of sample size (N) and effect size (ES) was observed on the level-2 parameters' rejection values (see Table 4.9). The rejection of the parameters increased from 0% at $N = 25$ to close to 100% at $N = 350$. It was also noticed that rejection at $ES = 0.60$ conditions were generally higher than that of the $ES = 0.30$ conditions, and rejection reached the acceptable magnitude (i.e., at least 0.80) for $ES = 0.60$ at $N = 100$ while $ES = 0.30$ was only acceptable when $N = 200$. There was also no substantial difference in the rejection across the levels of T and PMD , indicating that there may be no substantial effects of T and PMD .

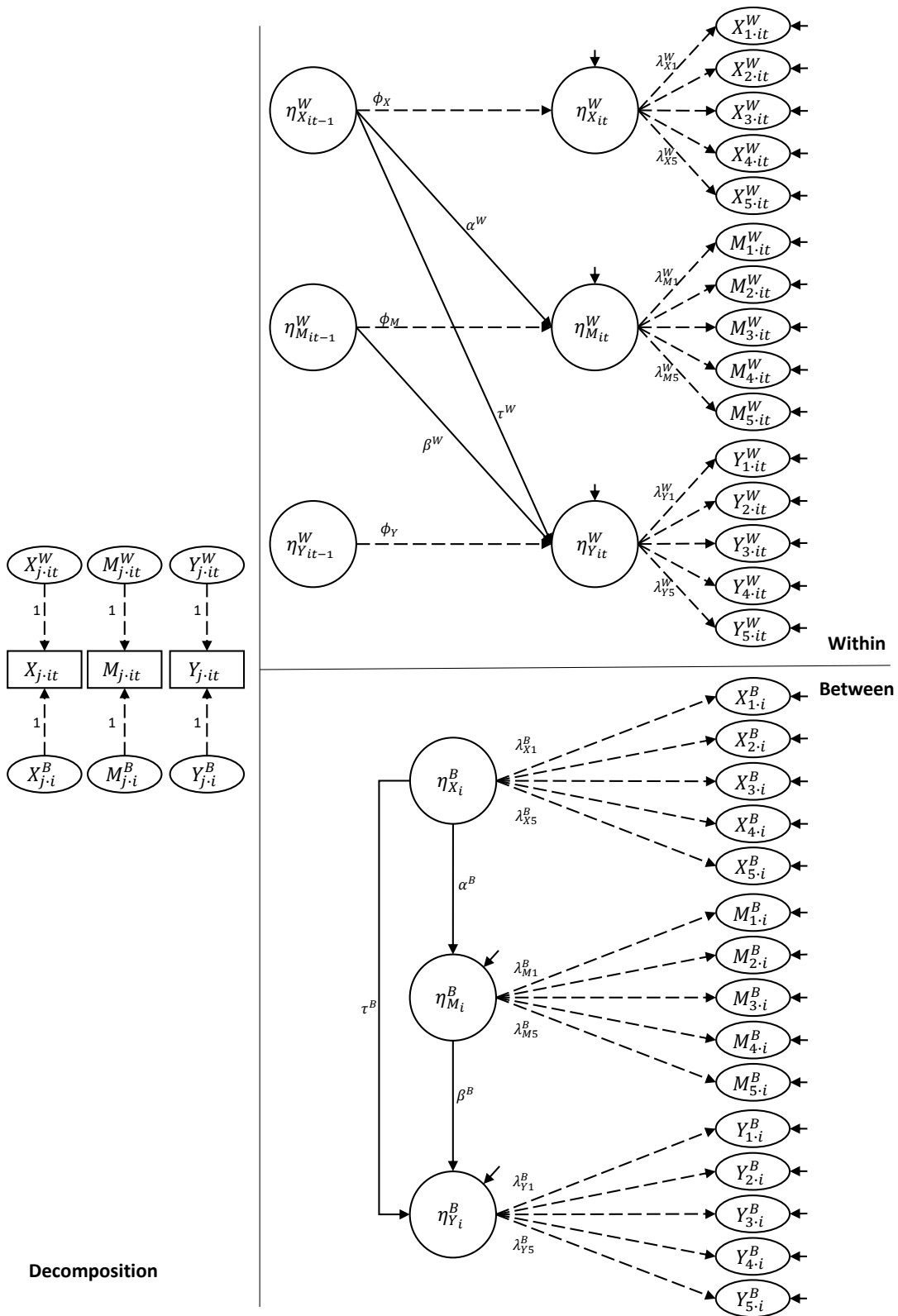


Figure 4.3.1: Data-Generating 1-1-1 Mediation Model

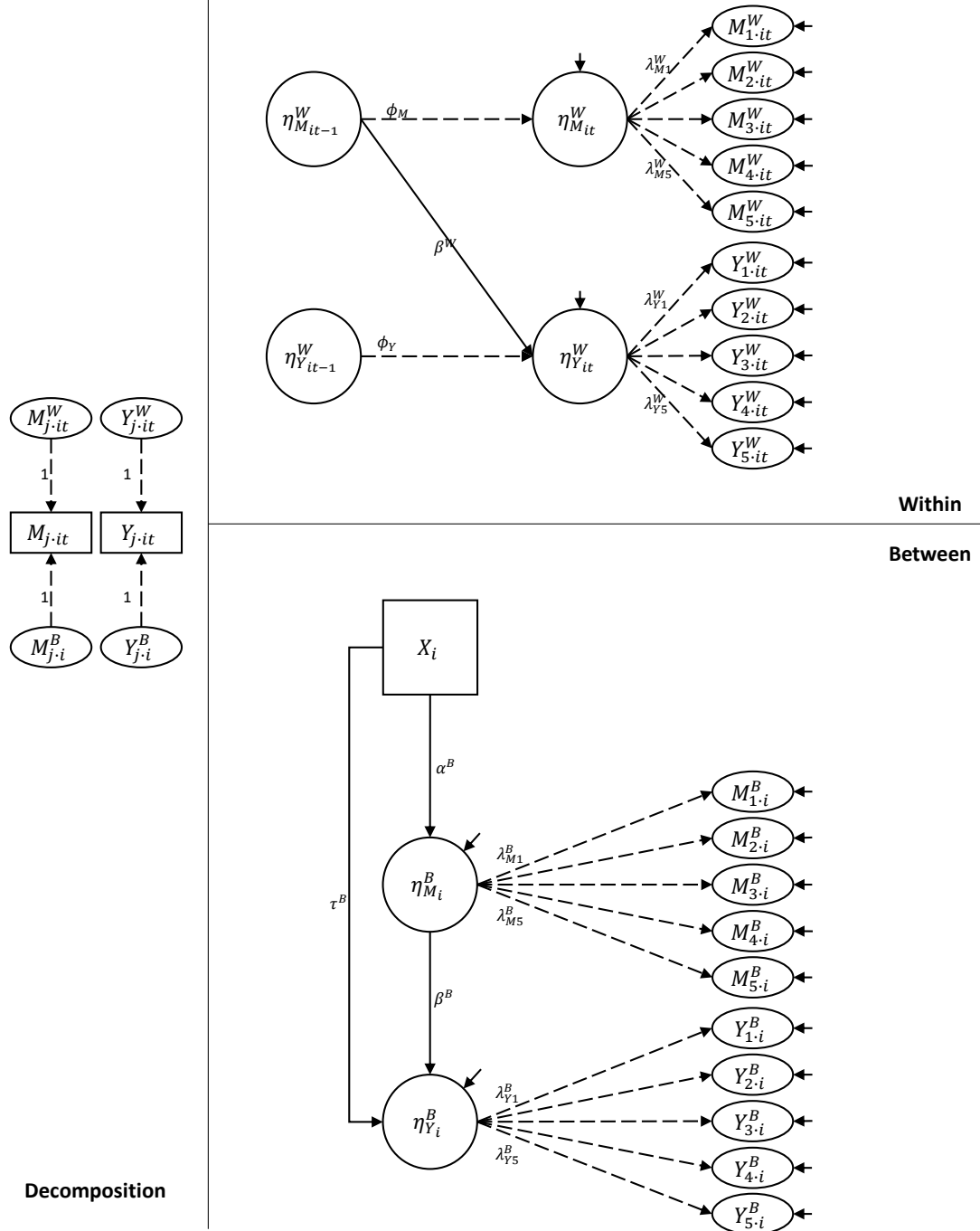


Figure 4.3.2: Data-Generating 2-1-1 Mediation Model

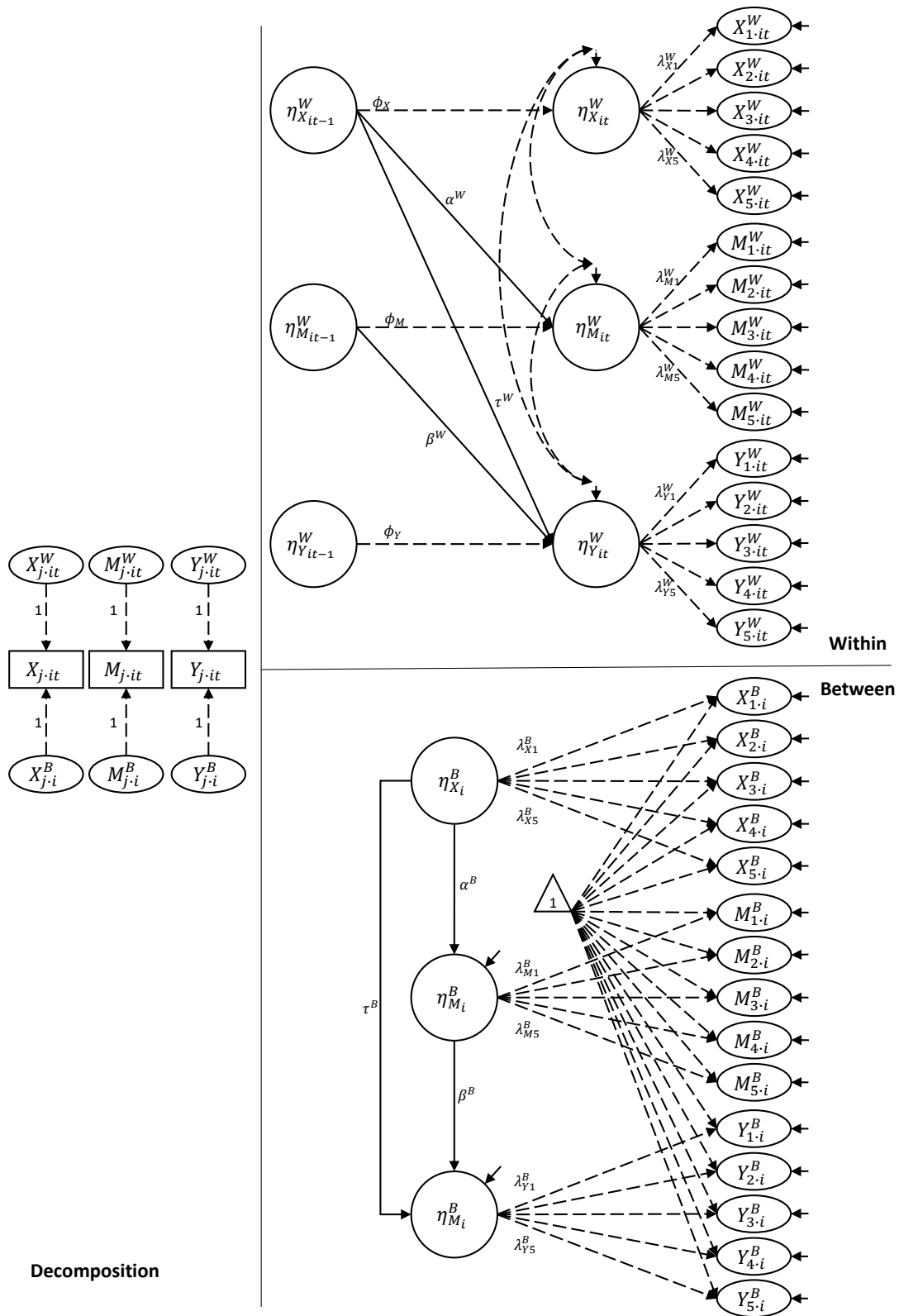


Figure 4.3.3: Fitted 1-1-1 Mediation Model

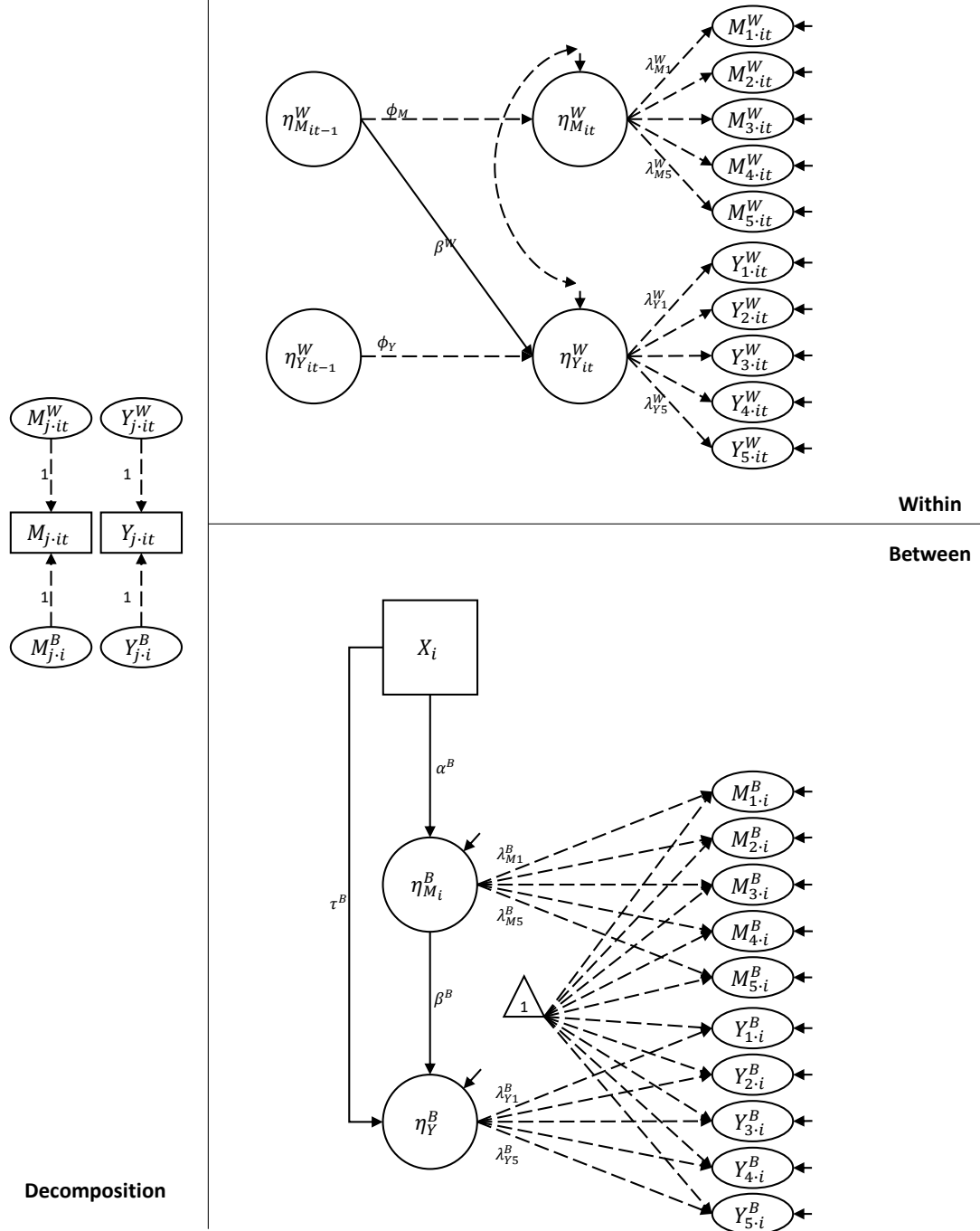


Figure 4.3.4: Fitted 2-1-1 Mediation Model

Table 4.4: 1-1-1 Mediation Model Level-1 Key Parameters Relative Bias

T	ES	PMD	N					
			25	50	100	200	350	
α^W								
30	0.3	0%	0.015 (0.136)	0.009 (0.103)	-0.008 (0.072)	-0.001 (0.050)	-0.004 (0.038)	
		20%	0.014 (0.149)	0.006 (0.099)	-0.008 (0.076)	-0.001 (0.051)	-0.003 (0.040)	
		40%	0.025 (0.166)	0.010 (0.111)	-0.007 (0.082)	-0.001 (0.057)	-0.004 (0.042)	
	0.6	0%	0.004 (0.050)	-0.009 (0.037)	-0.015 (0.026)	-0.016 (0.018)	-0.014 (0.014)	
		20%	0.004 (0.055)	-0.006 (0.041)	-0.014 (0.027)	-0.015 (0.019)	-0.013 (0.015)	
		40%	0.003 (0.059)	-0.004 (0.048)	-0.015 (0.030)	-0.014 (0.022)	-0.015 (0.017)	
	60	0.3	0%	-0.007 (0.096)	0.001 (0.067)	-0.004 (0.048)	-0.006 (0.034)	-0.003 (0.026)
			20%	-0.004 (0.102)	-0.001 (0.068)	-0.002 (0.050)	-0.006 (0.036)	-0.003 (0.028)
			40%	-0.003 (0.104)	0.002 (0.077)	0.000 (0.053)	-0.006 (0.038)	-0.004 (0.030)
0.6		0%	-0.013 (0.035)	-0.017 (0.026)	-0.014 (0.019)	-0.015 (0.013)	-0.015 (0.009)	
		20%	-0.012 (0.039)	-0.017 (0.026)	-0.013 (0.020)	-0.015 (0.014)	-0.015 (0.010)	
		40%	-0.013 (0.041)	-0.020 (0.031)	-0.014 (0.022)	-0.016 (0.015)	-0.015 (0.011)	
β^W								
30	0.3	0%	-0.018 (0.131)	-0.011 (0.095)	-0.016 (0.068)	-0.011 (0.046)	-0.016 (0.037)	
		20%	-0.018 (0.135)	-0.009 (0.102)	-0.014 (0.071)	-0.013 (0.048)	-0.016 (0.038)	
		40%	-0.032 (0.150)	-0.008 (0.104)	-0.019 (0.083)	-0.013 (0.051)	-0.015 (0.043)	
	0.6	0%	-0.124 (0.055)	-0.112 (0.041)	-0.106 (0.029)	-0.104 (0.020)	-0.104 (0.015)	
		20%	-0.128 (0.061)	-0.115 (0.044)	-0.102 (0.032)	-0.104 (0.022)	-0.104 (0.017)	
		40%	-0.136 (0.070)	-0.116 (0.052)	-0.107 (0.036)	-0.104 (0.025)	-0.104 (0.018)	
	60	0.3	0%	-0.013 (0.089)	-0.009 (0.061)	-0.016 (0.045)	-0.015 (0.034)	-0.016 (0.026)
			20%	-0.012 (0.093)	-0.010 (0.063)	-0.016 (0.048)	-0.015 (0.036)	-0.017 (0.028)
			40%	-0.015 (0.101)	-0.006 (0.069)	-0.015 (0.054)	-0.014 (0.037)	-0.017 (0.030)
0.6		0%	-0.109 (0.036)	-0.104 (0.027)	-0.104 (0.020)	-0.104 (0.013)	-0.104 (0.011)	
		20%	-0.109 (0.041)	-0.104 (0.030)	-0.104 (0.021)	-0.104 (0.014)	-0.104 (0.011)	
		40%	-0.110 (0.049)	-0.103 (0.033)	-0.105 (0.025)	-0.103 (0.017)	-0.103 (0.013)	
τ^W								
30	0.3	0%	-0.015 (0.127)	-0.015 (0.096)	-0.024 (0.068)	-0.021 (0.045)	-0.017 (0.036)	
		20%	-0.017 (0.136)	-0.016 (0.099)	-0.026 (0.071)	-0.022 (0.047)	-0.016 (0.037)	
		40%	-0.008 (0.151)	-0.022 (0.108)	-0.027 (0.075)	-0.020 (0.052)	-0.017 (0.039)	
	0.6	0%	-0.139 (0.044)	-0.125 (0.032)	-0.120 (0.024)	-0.117 (0.016)	-0.118 (0.012)	
		20%	-0.137 (0.048)	-0.124 (0.033)	-0.121 (0.026)	-0.118 (0.017)	-0.118 (0.013)	
		40%	-0.142 (0.054)	-0.129 (0.037)	-0.123 (0.029)	-0.117 (0.019)	-0.118 (0.015)	
	60	0.3	0%	-0.026 (0.093)	-0.017 (0.065)	-0.020 (0.044)	-0.021 (0.032)	-0.020 (0.025)
			20%	-0.023 (0.100)	-0.018 (0.065)	-0.021 (0.047)	-0.021 (0.035)	-0.021 (0.026)
			40%	-0.020 (0.109)	-0.026 (0.076)	-0.022 (0.052)	-0.022 (0.037)	-0.020 (0.027)
0.6		0%	-0.125 (0.031)	-0.120 (0.022)	-0.118 (0.016)	-0.119 (0.010)	-0.119 (0.008)	
		20%	-0.127 (0.036)	-0.119 (0.024)	-0.118 (0.017)	-0.119 (0.011)	-0.119 (0.009)	
		40%	-0.124 (0.038)	-0.121 (0.029)	-0.117 (0.020)	-0.119 (0.013)	-0.119 (0.010)	

Note: N = Sample Size; T = measurement occasions; ES = Effect Size, PMD = Planned-Missing Data Rate. See Figure 4.3.3 for the three parameters of interest α^W , β^W , and τ^W . The values without the parenthesis represent the mean parameter relative bias averaged across successful replications and the values within the parenthesis represent the standard deviation of the parameter relative bias across successful replications. Values that were not within the acceptable [-0.05 and 0.05] bound were in bold.

Table 4.5: 1-1-1 Mediation Model Level-2 Key Parameters Relative Bias

T	ES	PMD	N					
			25	50	100	200	350	
α^B								
30	0.3	0%	-0.800 (1.210)	-0.807 (0.490)	-0.102 (0.503)	-0.030 (0.285)	-0.017 (0.213)	
		20%	-0.989 (0.304)	-0.864 (0.379)	-0.089 (0.498)	-0.028 (0.285)	-0.017 (0.212)	
		40%	-1.020 (3.220)	-0.902 (0.422)	-0.135 (0.530)	-0.025 (0.288)	-0.019 (0.214)	
	0.6	0%	-0.900 (0.883)	-0.711 (0.494)	-0.059 (0.240)	-0.014 (0.120)	-0.005 (0.088)	
		20%	-0.930 (0.257)	-0.766 (0.460)	-0.042 (0.229)	-0.012 (0.121)	-0.007 (0.088)	
		40%	-0.598 (2.420)	-0.771 (0.517)	-0.073 (0.295)	-0.011 (0.122)	-0.007 (0.089)	
	60	0.3	0%	-1.270 (0.457)	-0.681 (0.588)	-0.060 (0.481)	-0.013 (0.285)	0.006 (0.222)
			20%	-0.961 (0.422)	-0.885 (0.585)	-0.086 (0.494)	-0.016 (0.286)	0.004 (0.223)
			40%	-0.724 (0.361)	-0.900 (0.378)	-0.071 (0.476)	-0.008 (0.288)	0.004 (0.225)
0.6		0%	-1.170 (0.308)	-0.551 (0.524)	-0.025 (0.199)	0.002 (0.104)	-0.005 (0.083)	
		20%	-1.030 (0.304)	-0.787 (0.550)	-0.032 (0.209)	0.001 (0.104)	-0.003 (0.084)	
		40%	-0.827 (0.260)	-0.709 (0.468)	-0.022 (0.192)	0.005 (0.106)	-0.004 (0.084)	
β^B								
30	0.3	0%	-0.898 (0.372)	-0.379 (0.690)	-0.046 (0.418)	-0.026 (0.311)	-0.034 (0.223)	
		20%	-0.951 (0.265)	-0.352 (0.691)	-0.077 (0.419)	-0.033 (0.313)	-0.033 (0.224)	
		40%	-0.938 (0.325)	-0.512 (0.678)	-0.045 (0.431)	-0.034 (0.319)	-0.035 (0.225)	
	0.6	0%	-0.939 (0.223)	-0.419 (0.510)	-0.151 (0.203)	-0.165 (0.125)	-0.166 (0.098)	
		20%	-0.969 (0.196)	-0.418 (0.507)	-0.166 (0.199)	-0.163 (0.128)	-0.168 (0.098)	
		40%	-0.950 (0.233)	-0.458 (0.518)	-0.153 (0.208)	-0.167 (0.133)	-0.168 (0.101)	
	60	0.3	0%	-0.944 (0.322)	-0.353 (0.650)	-0.058 (0.411)	-0.017 (0.297)	-0.012 (0.228)
			20%	-0.931 (0.354)	-0.281 (0.673)	-0.050 (0.400)	-0.014 (0.298)	-0.014 (0.228)
			40%	-0.996 (0.396)	-0.293 (0.677)	-0.047 (0.412)	-0.024 (0.296)	-0.017 (0.228)
0.6		0%	-0.974 (0.274)	-0.323 (0.451)	-0.153 (0.179)	-0.170 (0.124)	-0.158 (0.089)	
		20%	-0.927 (0.325)	-0.274 (0.482)	-0.157 (0.178)	-0.174 (0.124)	-0.160 (0.090)	
		40%	-0.989 (0.368)	-0.284 (0.475)	-0.146 (0.181)	-0.176 (0.127)	-0.161 (0.092)	
τ^B								
30	0.3	0%	-0.825 (0.492)	-0.769 (0.514)	-0.134 (0.462)	-0.067 (0.298)	-0.036 (0.230)	
		20%	-0.998 (0.025)	-0.870 (0.451)	-0.117 (0.467)	-0.070 (0.300)	-0.032 (0.230)	
		40%	-1.010 (0.162)	-0.865 (0.433)	-0.185 (0.503)	-0.055 (0.304)	-0.038 (0.234)	
	0.6	0%	-0.826 (0.400)	-0.743 (0.413)	-0.213 (0.239)	-0.167 (0.124)	-0.165 (0.096)	
		20%	-0.993 (0.049)	-0.846 (0.394)	-0.197 (0.226)	-0.168 (0.127)	-0.163 (0.097)	
		40%	-1.010 (0.121)	-0.803 (0.386)	-0.239 (0.281)	-0.162 (0.130)	-0.170 (0.099)	
	60	0.3	0%	-0.985 (0.151)	-0.624 (0.584)	-0.092 (0.420)	-0.059 (0.295)	-0.040 (0.207)
			20%	-0.989 (0.089)	-0.721 (0.542)	-0.106 (0.437)	-0.046 (0.295)	-0.041 (0.207)
			40%	-0.958 (0.176)	-0.800 (0.484)	-0.087 (0.415)	-0.056 (0.298)	-0.040 (0.211)
		0.6	0%	-0.989 (0.101)	-0.573 (0.451)	-0.188 (0.204)	-0.169 (0.122)	-0.170 (0.091)
			20%	-0.988 (0.111)	-0.722 (0.435)	-0.184 (0.206)	-0.160 (0.123)	-0.169 (0.092)
			40%	-0.962 (0.157)	-0.724 (0.406)	-0.190 (0.206)	-0.167 (0.126)	-0.167 (0.093)

Note: N = Sample Size; T = measurement occasions; ES = Effect Size, PMD = Planned-Missing Data Rate. See Figure 4.3.3 for the three parameters of interest α^B , β^B , and τ^B . The values without the parenthesis represent the mean parameter relative bias averaged across successful replications and the values within the parenthesis represent the standard deviation of the parameter relative bias across successful replications. Values that were not within the acceptable [-0.05 and 0.05] bound were in bold.

Table 4.6: 1-1-1 Mediation Model Level-1 Key Parameters Coverage

T	ES	PMD	N					
			25	50	100	200	350	
							α^W	
30	0.3	0%	0.892	0.883	0.893	0.886	0.882	
		20%	0.874	0.926	0.888	0.886	0.880	
		40%	0.863	0.906	0.881	0.870	0.886	
	0.6	0%	0.905	0.889	0.866	0.782	0.696	
		20%	0.896	0.885	0.877	0.798	0.712	
		40%	0.915	0.852	0.848	0.808	0.760	
	60	0.3	0%	0.901	0.906	0.882	0.884	0.888
			20%	0.889	0.904	0.891	0.890	0.880
			40%	0.909	0.881	0.896	0.880	0.864
0.6		0%	0.910	0.809	0.783	0.650	0.498	
		20%	0.882	0.847	0.831	0.682	0.550	
		40%	0.885	0.806	0.799	0.714	0.608	
							β^W	
30	0.3	0%	0.895	0.904	0.891	0.874	0.848	
		20%	0.903	0.900	0.899	0.898	0.836	
		40%	0.901	0.911	0.867	0.896	0.848	
	0.6	0%	0.250	0.126	0.013	0.000	0.000	
		20%	0.308	0.145	0.048	0.000	0.000	
		40%	0.410	0.239	0.068	0.006	0.000	
	60	0.3	0%	0.906	0.928	0.878	0.840	0.808
			20%	0.915	0.929	0.886	0.850	0.804
			40%	0.912	0.922	0.887	0.874	0.808
0.6		0%	0.092	0.009	0.000	0.000	0.000	
		20%	0.139	0.034	0.000	0.000	0.000	
		40%	0.246	0.077	0.004	0.000	0.000	
							τ^W	
30	0.3	0%	0.907	0.883	0.878	0.860	0.850	
		20%	0.903	0.897	0.857	0.872	0.866	
		40%	0.892	0.900	0.883	0.884	0.874	
	0.6	0%	0.070	0.012	0.000	0.000	0.000	
		20%	0.111	0.018	0.002	0.000	0.000	
		40%	0.164	0.039	0.000	0.000	0.000	
	60	0.3	0%	0.878	0.883	0.860	0.798	0.762
			20%	0.881	0.898	0.851	0.822	0.750
			40%	0.860	0.864	0.860	0.828	0.808
0.6		0%	0.002	0.003	0.000	0.000	0.000	
		20%	0.016	0.000	0.000	0.000	0.000	
		40%	0.033	0.000	0.000	0.000	0.000	

Note: N = Sample Size; T = measurement occasions; ES = Effect Size, PMD = Planned-Missing Data Rate. See Figure 4.3.3 for the three parameters of interest α^W , β^W , and τ^W . The values represent the coverage averaged across successful replications. Values that were smaller than the acceptable lower boundary of coverage (i.e., 0.87) were in bold.

Table 4.7: 1-1-1 Mediation Model Level-2 Key Parameters Coverage

T	ES	PMD	N					
			25	50	100	200	350	
α^B								
30	0.3	0%	0.997	0.970	0.893	0.916	0.910	
		20%	1.000	0.974	0.886	0.912	0.906	
		40%	0.997	0.994	0.879	0.914	0.910	
	0.6	0%	0.993	0.895	0.894	0.894	0.884	
		20%	0.989	0.894	0.881	0.890	0.890	
		40%	0.996	0.921	0.888	0.882	0.888	
	60	0.3	0%	1.000	0.964	0.844	0.880	0.892
			20%	1.000	0.948	0.858	0.880	0.890
			40%	1.000	0.986	0.868	0.878	0.878
0.6		0%	0.990	0.898	0.882	0.912	0.894	
		20%	0.992	0.858	0.882	0.920	0.886	
		40%	0.995	0.889	0.884	0.894	0.888	
β^B								
30	0.3	0%	0.990	0.948	0.909	0.880	0.904	
		20%	0.989	0.950	0.912	0.876	0.890	
		40%	0.995	0.953	0.906	0.884	0.898	
	0.6	0%	0.995	0.932	0.810	0.638	0.450	
		20%	0.978	0.920	0.799	0.650	0.454	
		40%	0.996	0.936	0.822	0.670	0.478	
	60	0.3	0%	0.998	0.958	0.889	0.896	0.870
			20%	0.987	0.959	0.904	0.890	0.876
			40%	0.990	0.950	0.891	0.894	0.882
0.6		0%	0.938	0.914	0.806	0.612	0.442	
		20%	0.941	0.943	0.804	0.590	0.442	
		40%	0.964	0.932	0.813	0.606	0.458	
τ^B								
30	0.3	0%	0.997	0.981	0.918	0.894	0.880	
		20%	0.989	0.974	0.931	0.892	0.882	
		40%	0.995	0.972	0.921	0.896	0.882	
	0.6	0%	0.993	0.868	0.772	0.614	0.460	
		20%	0.969	0.847	0.785	0.620	0.456	
		40%	0.985	0.894	0.784	0.664	0.470	
	60	0.3	0%	0.991	0.944	0.916	0.880	0.892
			20%	0.997	0.975	0.917	0.872	0.894
			40%	1.000	0.972	0.913	0.882	0.912
0.6		0%	0.898	0.830	0.747	0.618	0.374	
		20%	0.914	0.807	0.764	0.614	0.410	
		40%	0.951	0.795	0.734	0.624	0.440	

Note: N = Sample Size; T = measurement occasions; ES = Effect Size, PMD = Planned-Missing Data Rate. See Figure 4.3.3 for the three parameters of interest α^B , β^B , and τ^B . The values represent the coverage averaged across successful replications. Values that were smaller than the acceptable lower boundary of coverage (i.e., 0.87) were in bold.

Table 4.8: 1-1-1 Mediation Model Level-1 Key Parameters Rejection

T	ES	PMD	N					
			25	50	100	200	350	
α^W								
30	0.3	0%	1.000	1.000	1.000	1.000	1.000	
		20%	1.000	1.000	1.000	1.000	1.000	
		40%	1.000	1.000	1.000	1.000	1.000	
	0.6	0%	1.000	1.000	1.000	1.000	1.000	
		20%	1.000	1.000	1.000	1.000	1.000	
		40%	1.000	1.000	1.000	1.000	1.000	
	60	0.3	0%	1.000	1.000	1.000	1.000	1.000
			20%	1.000	1.000	1.000	1.000	1.000
			40%	1.000	1.000	1.000	1.000	1.000
0.6		0%	1.000	1.000	1.000	1.000	1.000	
		20%	1.000	1.000	1.000	1.000	1.000	
		40%	1.000	1.000	1.000	1.000	1.000	
β^W								
30	0.3	0%	1.000	1.000	1.000	1.000	1.000	
		20%	1.000	1.000	1.000	1.000	1.000	
		40%	1.000	1.000	1.000	1.000	1.000	
	0.6	0%	1.000	1.000	1.000	1.000	1.000	
		20%	1.000	1.000	1.000	1.000	1.000	
		40%	1.000	1.000	1.000	1.000	1.000	
	60	0.3	0%	1.000	1.000	1.000	1.000	1.000
			20%	1.000	1.000	1.000	1.000	1.000
			40%	1.000	1.000	1.000	1.000	1.000
0.6		0%	1.000	1.000	1.000	1.000	1.000	
		20%	1.000	1.000	1.000	1.000	1.000	
		40%	1.000	1.000	1.000	1.000	1.000	
τ^W								
30	0.3	0%	1.000	1.000	1.000	1.000	1.000	
		20%	1.000	1.000	1.000	1.000	1.000	
		40%	1.000	1.000	1.000	1.000	1.000	
	0.6	0%	1.000	1.000	1.000	1.000	1.000	
		20%	1.000	1.000	1.000	1.000	1.000	
		40%	1.000	1.000	1.000	1.000	1.000	
	60	0.3	0%	1.000	1.000	1.000	1.000	1.000
			20%	1.000	1.000	1.000	1.000	1.000
			40%	1.000	1.000	1.000	1.000	1.000
0.6		0%	1.000	1.000	1.000	1.000	1.000	
		20%	1.000	1.000	1.000	1.000	1.000	
		40%	1.000	1.000	1.000	1.000	1.000	

Note: N = Sample Size; T = measurement occasions; ES = Effect Size, PMD = Planned-Missing Data Rate. See Figure 4.3.3 for the three parameters of interest α^W , β^W , and τ^W . The values represent the rejection averaged across successful replications.

Table 4.9: 1-1-1 Mediation Model Level-2 Key Parameters Rejection

T	ES	PMD	N					
			25	50	100	200	350	
α^B								
30	0.3	0%	0.000	0.063	0.526	0.870	0.976	
		20%	0.000	0.037	0.531	0.862	0.976	
		40%	0.000	0.025	0.519	0.872	0.974	
	0.6	0%	0.000	0.169	0.923	1.000	1.000	
		20%	0.000	0.168	0.950	1.000	1.000	
		40%	0.000	0.145	0.907	1.000	1.000	
	60	0.3	0%	0.000	0.108	0.598	0.876	0.984
			20%	0.000	0.088	0.578	0.872	0.984
			40%	0.002	0.025	0.589	0.882	0.984
0.6		0%	0.000	0.309	0.971	1.000	1.000	
		20%	0.000	0.224	0.960	1.000	1.000	
		40%	0.003	0.182	0.985	1.000	1.000	
β^B								
30	0.3	0%	0.010	0.191	0.560	0.834	0.960	
		20%	0.005	0.198	0.541	0.824	0.964	
		40%	0.005	0.114	0.544	0.804	0.960	
	0.6	0%	0.011	0.391	0.962	1.000	1.000	
		20%	0.009	0.383	0.952	1.000	1.000	
		40%	0.013	0.312	0.947	1.000	1.000	
	60	0.3	0%	0.005	0.200	0.589	0.846	0.976
			20%	0.013	0.231	0.573	0.870	0.976
			40%	0.012	0.233	0.600	0.844	0.972
0.6		0%	0.022	0.559	0.964	1.000	1.000	
		20%	0.038	0.595	0.968	1.000	1.000	
		40%	0.039	0.567	0.973	1.000	1.000	
τ^B								
30	0.3	0%	0.000	0.079	0.503	0.802	0.958	
		20%	0.000	0.055	0.488	0.798	0.960	
		40%	0.000	0.039	0.458	0.792	0.960	
	0.6	0%	0.000	0.191	0.891	1.000	1.000	
		20%	0.000	0.156	0.918	1.000	1.000	
		40%	0.002	0.145	0.861	1.000	1.000	
	60	0.3	0%	0.002	0.136	0.582	0.832	0.978
			20%	0.000	0.115	0.582	0.840	0.972
			40%	0.002	0.078	0.568	0.810	0.968
0.6		0%	0.000	0.333	0.952	1.000	1.000	
		20%	0.005	0.215	0.941	1.000	1.000	
		40%	0.010	0.177	0.959	1.000	1.000	

Note: N = Sample Size; T = measurement occasions; ES = Effect Size, PMD = Planned-Missing Data Rate. See Figure 4.3.3 for the three parameters of interest α^B , β^B , and τ^B . The values represent the rejection averaged across successful replications. Values that were smaller than the acceptable lower boundary of rejection (i.e., 0.80) were in bold.

4.4.2 2-1-1 Mediation Model

Convergence Rate

Similar to the simulations for the 1-1-1 mediation model, the convergence rate approached 100% as sample size (N) increased (see Table 4.10). The convergence rate for all conditions were higher than 90% at $N = 100$ and were mostly 100% at $N = 200$. There was no specific pattern of effect of the other experimental factors (i.e., measurement occasion T , effect size ES , and planned-missing data PMD) considered in this simulation study.

Table 4.10: 2-1-1 Mediation Model Convergence Rate for 500 Replications

T	ES	PMD	N					
			25	50	100	200	350	
30	0.3	0%	0.872	0.860	0.972	1.000	1.000	
		20%	0.840	0.608	0.962	1.000	1.000	
		40%	0.912	0.844	0.954	1.000	1.000	
	0.6	0%	0.868	0.770	0.936	0.994	1.000	
		20%	0.740	0.502	0.930	1.000	1.000	
		40%	0.882	0.826	0.904	1.000	1.000	
	60	0.3	0%	0.854	0.788	0.980	1.000	1.000
			20%	0.906	0.852	0.990	1.000	1.000
			40%	0.926	0.834	0.992	1.000	1.000
0.6		0%	0.844	0.776	0.866	1.000	1.000	
		20%	0.916	0.754	0.928	1.000	1.000	
		40%	0.914	0.816	0.970	1.000	1.000	

Note: N = Sample Size; T = measurement occasions; ES = Effect Size, PMD = Planned-Missing Data Rate. The values represent the proportion of converged replications out of the 500 total replications for each combination of conditions (e.g., 1 = all 500 replications converged successfully; 0.80 = 400 out of 500 replications converged successfully).

Relative Bias

Inspection of Table 4.11 for the level-1 parameter (β^W ; effect of lag-1 M on Y) showed that the relative bias was all within the acceptable range. Similar to the pattern in the 1-1-1 mediation model relative bias results, there was a general larger relative bias for the larger effect size ($ES = 0.60$) condition compared to the smaller effect size

($ES = 0.030$) condition. Similarly, the variability (quantified by the standard deviation presented within the brackets in Table 4.11) decreased with an increase of N from the left columns to the right columns.

For each parameter at each combination of the experimental factors (i.e., T , ES and N), a comparison of the relative bias values of the $PMD = 20\%$ and 40% levels were highly similar to the relative bias at $PMD = 0\%$, hence an indication that there was no substantial effect of missing data. For each parameter at each combination of the experimental factors (i.e., ES , PMD , and N), a comparison of the relative bias values of the $T = 30$ were similar to the relative bias at $T = 60$, indicating a lack of effect of measurement occasions (T) on the relative bias. These findings were highly similar of the results in the level-1 parameters of the 1-1-1 mediation model.

Comparing to the 1-1-1 mediation model parameters which were generally systematically under-estimated, the direction of the relative bias for the level-2 (between person) parameters (see Table 4.12) were mixed, with under-estimation occurred in some simulation conditions and over-estimation in others.

Similar to the results on the level-1 parameters, the magnitude of relative bias in the level-2 parameters was not greatly affected by the amount of missing data (PMD) and measurement occasions (T). The relative bias was generally out of the acceptable boundary of -0.05 and 0.05 at the small sample size conditions ($N = 25, 50, \text{ and } 100$) in most combinations of the experimental factors, especially for the β^B (i.e., effect of M on Y). In general, with an increase in sample size, the parameter relative bias tend to decrease for the parameters in general, except for τ^B (i.e., effect of X on Y) which remained relatively constant at each level of N .

The effect of ES was also similar to that of the level-1 parameters in that condition of larger effect size ($ES = 0.60$) showed a larger relative bias (either under-estimation or over-estimation) in general comparing with the conditions with smaller effect size ($ES = 0.30$), and this observation was only true for τ^B and α^B (i.e., effect of X on M).

Table 4.11: 2-1-1 Mediation Model Level-1 Key Parameter Relative Bias

T	ES	PMD	N					
			25	50	100	200	350	
			β^W					
30	0.3	0%	0.001 (0.134)	-0.013 (0.097)	-0.003 (0.068)	-0.004 (0.049)	-0.007 (0.036)	
		20%	0.001 (0.145)	-0.005 (0.103)	0.002 (0.071)	-0.004 (0.051)	-0.007 (0.038)	
		40%	0.007 (0.156)	-0.009 (0.112)	0.001 (0.079)	-0.005 (0.054)	-0.006 (0.041)	
	0.6	0%	-0.014 (0.051)	-0.014 (0.038)	-0.016 (0.025)	-0.018 (0.018)	-0.014 (0.014)	
		20%	-0.014 (0.053)	-0.011 (0.043)	-0.016 (0.027)	-0.018 (0.019)	-0.014 (0.015)	
		40%	-0.013 (0.062)	-0.014 (0.045)	-0.014 (0.031)	-0.019 (0.022)	-0.015 (0.016)	
	60	0.3	0%	0.001 (0.096)	-0.005 (0.066)	-0.005 (0.046)	-0.003 (0.036)	-0.005 (0.026)
			20%	0.000 (0.099)	-0.006 (0.069)	-0.006 (0.048)	-0.003 (0.036)	-0.005 (0.027)
			40%	-0.005 (0.110)	-0.007 (0.073)	-0.005 (0.050)	-0.003 (0.039)	-0.005 (0.029)
0.6		0%	-0.013 (0.037)	-0.018 (0.027)	-0.017 (0.019)	-0.015 (0.012)	-0.016 (0.010)	
		20%	-0.014 (0.039)	-0.018 (0.027)	-0.017 (0.020)	-0.015 (0.013)	-0.016 (0.010)	
		40%	-0.016 (0.044)	-0.016 (0.031)	-0.016 (0.023)	-0.015 (0.015)	-0.015 (0.011)	

Note: N = Sample Size; T = measurement occasions; ES = Effect Size, PMD = Planned-Missing Data Rate. See Figure 4.3.4 for the parameters of interest β^W . The values without the parenthesis represent the mean parameter relative bias averaged across successful replications and the values within the parenthesis represent the standard deviation of the parameter relative bias across successful replications. Values that were not within the acceptable [-0.05 and 0.05] bound were in bold.

Coverage

Similar to the 1-1-1 mediation model results, substantial effect of measurement occasions (T) and planned-missing data (PMD) was not observed in the coverage of the level-1 (between time) parameters (see Table 4.13) and the level-2 (between person) parameters (see Table 4.14). For the level-1 parameter β^W , the coverage generally decreased with an increase of sample size from $N = 25$ to $N = 350$ for all parameters of interest regardless of combination of other experimental factors (i.e. T , ES , and PMD). It was also observed that the coverage of the parameters at $ES = 0.60$ was generally lower than those at the $ES = 0.30$ conditions. The parameter coverage in the $ES = 0.60$ condition were generally lower than the acceptable rate of 0.87, except at the $N = 25$ condition.

The level-2 parameters also showed the same effect of N and ES , where the coverage generally decreased with an increased of sample size and that the coverage at $ES = 0.60$ was generally lower than those in the $ES = 0.3$ condition. It was also observed that the coverage of the parameters were within the acceptable rate for almost all conditions for the β^B parameter and when $N = 25$ and 50 for the other two parameters (α^B and τ^B).

Rejection

The results were highly similar to that of the 1-1-1 mediation model for both the level-1 and level-2 parameters of interest. The level-1 parameter (β^W) of the 2-1-1 model (see Table 4.15) had a rejection of 1 (i.e. 100%) under all combinations of simulation conditions of sample size (N), measurement occasion (T), effect size (ES), and planned-missing data (PMD), suggesting an absence of effect of these experimental factors on the parameter rejection.

In contrast, the rejection of the level-2 parameters increased from 0% at $N = 25$ to close to 100% at $N = 350$ regardless of the other experimental factors for the β^B . This was only true for α^B and τ^W at the $ES = 0.60$ condition. In general, rejection at the $ES = 0.60$ condition was generally higher than that of the $ES = 0.30$ condition. It was also observed that the rejection did not reach an acceptable rate (0.80) for $N = 25$ and 50 conditions for all parameters.

Table 4.12: 2-1-1 Mediation Model Level-2 Key Parameters Relative Bias

T	ES	PMD	N					
			25	50	100	200	350	
α^B								
30	0.3	0%	-0.333 (1.000)	-0.153 (1.040)	0.073 (0.785)	0.010 (0.559)	0.055 (0.403)	
		20%	-0.711 (0.988)	-0.639 (1.120)	0.050 (0.778)	0.038 (0.558)	0.050 (0.403)	
		40%	-0.314 (0.918)	-0.573 (1.070)	0.030 (0.793)	0.001 (0.563)	0.040 (0.404)	
	0.6	0%	-0.608 (0.743)	-0.229 (0.750)	0.142 (0.371)	0.162 (0.261)	0.187 (0.196)	
		20%	-0.739 (0.690)	-0.737 (0.921)	0.131 (0.367)	0.172 (0.261)	0.182 (0.196)	
		40%	-0.498 (0.675)	-0.686 (0.878)	0.088 (0.452)	0.148 (0.265)	0.178 (0.198)	
	60	0.3	0%	-0.375 (1.030)	-0.342 (0.997)	0.023 (0.775)	0.019 (0.537)	0.007 (0.399)
			20%	-0.892 (1.040)	-0.319 (0.991)	0.132 (0.768)	0.004 (0.540)	0.060 (0.395)
			40%	-1.010 (1.070)	-0.278 (0.984)	0.022 (0.774)	-0.013 (0.547)	0.005 (0.401)
0.6		0%	-0.479 (0.742)	-0.266 (0.786)	0.137 (0.412)	0.161 (0.264)	0.156 (0.185)	
		20%	-0.952 (0.742)	-0.349 (0.803)	0.195 (0.368)	0.150 (0.267)	0.179 (0.184)	
		40%	-1.160 (0.863)	-0.341 (0.752)	0.145 (0.372)	0.152 (0.267)	0.159 (0.186)	
β^B								
30		0.3	0%	-0.849 (0.512)	-0.301 (0.712)	-0.054 (0.464)	-0.029 (0.305)	-0.016 (0.222)
			20%	-0.864 (0.424)	-0.534 (0.775)	-0.051 (0.464)	-0.032 (0.309)	-0.015 (0.223)
	40%		-0.858 (0.451)	-0.506 (0.710)	-0.068 (0.472)	-0.031 (0.312)	-0.017 (0.224)	
	0.6	0%	-0.893 (0.398)	-0.429 (0.514)	-0.036 (0.195)	-0.019 (0.131)	-0.008 (0.101)	
		20%	-0.898 (0.341)	-0.751 (0.644)	-0.032 (0.205)	-0.016 (0.134)	-0.006 (0.102)	
		40%	-0.840 (0.352)	-0.631 (0.557)	-0.070 (0.297)	-0.018 (0.135)	-0.011 (0.103)	
	60	0.3	0%	-0.809 (0.611)	-0.300 (0.634)	-0.044 (0.418)	-0.015 (0.285)	0.019 (0.194)
			20%	-0.852 (0.496)	-0.400 (0.708)	-0.034 (0.415)	-0.006 (0.284)	0.022 (0.195)
			40%	-0.879 (0.494)	-0.394 (0.662)	-0.049 (0.419)	-0.011 (0.289)	0.020 (0.196)
0.6		0%	-0.792 (0.438)	-0.310 (0.533)	-0.053 (0.224)	-0.016 (0.125)	-0.012 (0.096)	
		20%	-0.882 (0.373)	-0.432 (0.587)	-0.032 (0.181)	-0.010 (0.127)	-0.010 (0.096)	
		40%	-1.020 (0.369)	-0.464 (0.562)	-0.041 (0.177)	-0.015 (0.129)	-0.009 (0.097)	
τ^B								
30		0.3	0%	0.022 (1.390)	-0.130 (1.080)	-0.018 (0.770)	0.058 (0.524)	0.027 (0.398)
			20%	-0.014 (1.420)	-0.186 (1.090)	-0.031 (0.769)	0.078 (0.526)	0.017 (0.397)
	40%		0.003 (1.410)	-0.121 (1.090)	0.023 (0.784)	0.045 (0.532)	0.066 (0.403)	
	0.6	0%	0.020 (0.794)	0.184 (0.523)	0.137 (0.342)	0.154 (0.240)	0.145 (0.187)	
		20%	-0.034 (0.823)	0.221 (0.534)	0.131 (0.338)	0.166 (0.242)	0.145 (0.187)	
		40%	0.033 (0.798)	0.226 (0.527)	0.170 (0.348)	0.163 (0.243)	0.159 (0.191)	
	60	0.3	0%	-0.216 (1.320)	0.041 (1.020)	-0.005 (0.699)	-0.002 (0.524)	-0.029 (0.382)
			20%	-0.103 (1.360)	0.086 (1.010)	-0.014 (0.705)	0.019 (0.521)	-0.043 (0.382)
			40%	-0.107 (1.320)	0.150 (0.969)	-0.004 (0.702)	0.049 (0.522)	-0.040 (0.383)
0.6		0%	-0.009 (0.757)	0.162 (0.495)	0.151 (0.320)	0.137 (0.236)	0.157 (0.187)	
		20%	0.159 (0.672)	0.152 (0.496)	0.150 (0.318)	0.142 (0.238)	0.146 (0.187)	
		40%	0.083 (0.698)	0.161 (0.506)	0.162 (0.323)	0.154 (0.238)	0.151 (0.189)	

Note: N = Sample Size; T = measurement occasions; ES = Effect Size, PMD = Planned-Missing Data Rate. See Figure 4.3.4 for the three parameters of interest α^B , β^B , and τ^B . The values without the parenthesis represent the mean parameter relative bias averaged across successful replications and the values within the parenthesis represent the standard deviation of the parameter relative bias across successful replications. Values that were not within the acceptable [-0.05 and 0.05] bound were in bold.

Table 4.13: 2-1-1 Mediation Model Level-1 Key Parameter Coverage

T	ES	PMD	N				
			25	50	100	200	350
β^W							
30	0.3	0%	0.913	0.895	0.920	0.896	0.874
		20%	0.886	0.878	0.909	0.890	0.890
		40%	0.897	0.896	0.883	0.904	0.890
	0.6	0%	0.908	0.865	0.859	0.740	0.710
		20%	0.908	0.861	0.856	0.772	0.736
		40%	0.907	0.869	0.874	0.778	0.758
60	0.3	0%	0.904	0.909	0.896	0.856	0.890
		20%	0.894	0.901	0.909	0.890	0.900
		40%	0.886	0.899	0.911	0.886	0.886
	0.6	0%	0.898	0.784	0.732	0.686	0.472
		20%	0.878	0.801	0.746	0.720	0.530
		40%	0.877	0.853	0.784	0.730	0.610

Note: N = Sample Size; T = measurement occasions; ES = Effect Size, PMD = Planned-Missing Data Rate. See Figure 4.3.4 for the parameter of interest β^W . The values represent the coverage averaged across successful replications. Values that were smaller than the acceptable lower boundary of coverage (i.e., 0.87) were in bold.

Table 4.14: 2-1-1 Mediation Model Level-2 Key Parameters Coverage

T	ES	PMD	N					
			25	50	100	200	350	
α^B								
30	0.3	0%	0.989	0.942	0.868	0.874	0.912	
		20%	0.990	0.964	0.877	0.892	0.898	
		40%	0.996	0.962	0.855	0.866	0.902	
	0.6	0%	0.979	0.943	0.855	0.803	0.724	
		20%	0.989	0.948	0.877	0.796	0.734	
		40%	0.993	0.959	0.858	0.796	0.734	
	60	0.3	0%	0.984	0.939	0.873	0.866	0.870
			20%	0.985	0.948	0.863	0.874	0.876
			40%	0.991	0.959	0.865	0.872	0.876
0.6		0%	0.991	0.905	0.859	0.782	0.758	
		20%	1.000	0.923	0.828	0.802	0.728	
		40%	0.998	0.936	0.843	0.818	0.774	
β^B								
30	0.3	0%	0.993	0.912	0.860	0.892	0.914	
		20%	0.998	0.921	0.863	0.892	0.910	
		40%	0.998	0.931	0.870	0.894	0.894	
	0.6	0%	0.993	0.945	0.917	0.907	0.888	
		20%	0.997	0.912	0.910	0.896	0.888	
		40%	0.998	0.954	0.912	0.902	0.882	
	60	0.3	0%	0.979	0.954	0.902	0.892	0.928
			20%	0.993	0.925	0.897	0.886	0.922
			40%	0.991	0.954	0.899	0.884	0.932
0.6		0%	0.995	0.930	0.915	0.874	0.886	
		20%	0.996	0.944	0.903	0.886	0.874	
		40%	0.998	0.941	0.913	0.878	0.882	
τ^B								
30	0.3	0%	0.972	0.916	0.895	0.902	0.892	
		20%	0.964	0.924	0.890	0.896	0.896	
		40%	0.974	0.927	0.876	0.920	0.896	
	0.6	0%	0.995	0.930	0.876	0.861	0.810	
		20%	0.995	0.916	0.884	0.840	0.786	
		40%	0.998	0.961	0.869	0.848	0.762	
	60	0.3	0%	0.977	0.921	0.908	0.894	0.918
			20%	0.989	0.927	0.901	0.898	0.896
			40%	0.994	0.926	0.917	0.902	0.904
		0.6	0%	0.988	0.948	0.882	0.834	0.732
			20%	0.993	0.963	0.877	0.814	0.736
			40%	0.998	0.931	0.876	0.822	0.756

Note: N = Sample Size; T = measurement occasions; ES = Effect Size, PMD = Planned-Missing Data Rate. See Figure 4.3.4 for the three parameters of interest α^B , β^B , and τ^B . The values represent the coverage averaged across successful replications. Values that were smaller than the acceptable lower boundary of coverage (i.e., 0.87) were in bold.

Table 4.15: 2-1-1 Mediation Model Level-1 Key Parameter Rejection

T	ES	PMD	N				
			25	50	100	200	350
					beta		
30	0.3	0%	1.000	1.000	1.000	1.000	1.000
		20%	1.000	1.000	1.000	1.000	1.000
		40%	0.998	1.000	1.000	1.000	1.000
	0.6	0%	1.000	1.000	1.000	1.000	1.000
		20%	1.000	1.000	1.000	1.000	1.000
		40%	1.000	1.000	1.000	1.000	1.000
60	0.3	0%	1.000	1.000	1.000	1.000	1.000
		20%	1.000	1.000	1.000	1.000	1.000
		40%	1.000	1.000	1.000	1.000	1.000
	0.6	0%	1.000	1.000	1.000	1.000	1.000
		20%	1.000	1.000	1.000	1.000	1.000
		40%	1.000	1.000	1.000	1.000	1.000

Note: N = Sample Size; T = measurement occasions; ES = Effect Size, PMD = Planned-Missing Data Rate. See Figure 4.3.4 for the parameter of interest β^W . The values represent the rejection averaged across successful replications.

Table 4.16: 2-1-1 Mediation Model Level-2 Key Parameters Rejection

T	ES	PMD	N					
			25	50	100	200	350	
							α^B	
30	0.3	0%	0.028	0.142	0.333	0.468	0.706	
		20%	0.010	0.105	0.324	0.478	0.698	
		40%	0.009	0.078	0.331	0.470	0.680	
	0.6	0%	0.035	0.299	0.880	0.988	1.000	
		20%	0.019	0.175	0.862	0.984	1.000	
		40%	0.014	0.172	0.865	0.986	1.000	
	60	0.3	0%	0.016	0.114	0.335	0.510	0.684
			20%	0.013	0.124	0.380	0.450	0.710
			40%	0.011	0.144	0.331	0.442	0.656
0.6		0%	0.031	0.312	0.836	0.992	1.000	
		20%	0.011	0.297	0.888	0.988	1.000	
		40%	0.015	0.275	0.874	0.988	1.000	
							β^B	
30		0.3	0%	0.018	0.237	0.545	0.816	0.964
			20%	0.012	0.181	0.549	0.818	0.964
	40%		0.015	0.161	0.518	0.804	0.962	
	0.6	0%	0.030	0.384	0.970	1.000	1.000	
		20%	0.019	0.251	0.974	1.000	1.000	
		40%	0.009	0.218	0.940	1.000	1.000	
	60	0.3	0%	0.042	0.218	0.610	0.888	0.994
			20%	0.016	0.232	0.614	0.894	0.994
			40%	0.024	0.218	0.593	0.882	0.992
0.6		0%	0.031	0.412	0.933	1.000	1.000	
		20%	0.015	0.377	0.976	1.000	1.000	
		40%	0.011	0.358	0.988	1.000	1.000	
							τ^B	
30	0.3	0%	0.030	0.126	0.280	0.514	0.698	
		20%	0.055	0.128	0.289	0.532	0.678	
		40%	0.031	0.104	0.306	0.486	0.708	
	0.6	0%	0.053	0.444	0.895	0.994	1.000	
		20%	0.105	0.418	0.895	0.992	1.000	
		40%	0.086	0.324	0.894	0.992	1.000	
	60	0.3	0%	0.056	0.193	0.320	0.500	0.620
			20%	0.049	0.188	0.329	0.522	0.634
			40%	0.019	0.206	0.282	0.530	0.626
0.6		0%	0.102	0.572	0.901	0.998	1.000	
		20%	0.079	0.459	0.920	0.998	1.000	
		40%	0.039	0.449	0.909	0.994	1.000	

Note: N = Sample Size; T = measurement occasions; ES = Effect Size, PMD = Planned-Missing Data Rate. See Figure 4.3.4 for the three parameters of interest α^B , β^B , and τ^B . The values represent the rejection averaged across successful replications. Values that were smaller than the acceptable lower boundary of rejection (i.e. 0.80) were in bold.

4.5 Summary and Discussion

The objective of this study was to evaluate the effect of sample size, measurement occasion, effect size, and extend of planned-missing data on the parameter estimates of autoregressive multilevel mediation models with latent variables at both level-1 and level-2 components of the model. The results suggested that there was no substantial effect of planned-missing data (*PMD*) and measurement occasions (*T*) considered in this simulation on the parameter estimates. The relative bias, coverage, and rejection of the parameters of interest were highly similar across the levels of *PMD* and *T* in the simulation design.

This firstly suggests that researcher could consider implementing planned-missing data such as the three-form design for multiple-item questionnaires in applied research without sacrificing precision on the parameter estimates substantially as showed in the results comparing the conditions with and without missing-data. Secondly, the results also suggest that longer measurement occasions may not necessarily provide more accurate estimation than a shorter measurement occasion. However, it should be pointed out that the current simulation only considered $T = 30$ and 60 , unlike Schultzberg and Muthén (2018) which considered a wider range of measurement occasions.

Sample size (e.g., individuals) is one of the factors that would play a role in parameter bias, coverage and rejection. The effect of sample size on relative bias was mostly observed at the level-2 (between-individual) parameters. The relative bias decreased with an increase of sample size, indicating that a larger sample size would provide a more precise point-estimate. The results suggested that with a larger sample size, the 90% HDIs would be smaller which indicates higher precision. This can be inferred from the higher parameter rejection in larger sample size conditions. With a smaller (more precise) HDI for a parameter which has a non-zero value as the most probable value (e.g., simulated non-zero true value), the likelihood of a zero null value to be included in the HDI would be smaller as well, which translate to a higher rejection. This finding shows the external validity of Silvia et al.'s (2014) findings on the effect of sample size that extends beyond the maximum likelihood estimator to the Bayesian

MCMC Gibbs Sampling procedure.

The results also showed that with an increase in sample size, the coverage would decrease (i.e., the 90% HDI does not contain the true value) especially in the $ES = 0.60$ condition. I attribute this pattern to the unexpected finding on the high parameter relative bias of the $ES = 0.60$ conditions. With high relative bias, the parameters would be either under- or over-estimated, therefore deviates from the true value that was used to simulate the data. Pairing the precision in HDI that comes with higher sample size with the parameter bias would lead to a lower coverage for these conditions. For an instance, if a particular parameter is largely under-estimated and with a larger sample size, I would expect the corresponding HDI to narrowly cluster around the under-estimated parameter, causing the HDI to not include the true value. The reverse is also true in that with a smaller sample size, I would expect a wider HDI (i.e., lacking precision), therefore even though a parameter could be under-estimated, but the HDI would be wider to the extent that it also contain the true value (and also the ROPE).

As described above, one of the unexpected findings was the larger relative bias observed in the larger effect size condition as compared to the smaller effect size condition. The other unexpected findings was the observation that the relative bias also depended on the "location" of the variables associated to the parameter (i.e., relationship between predictor and the mediator α , between mediator and the outcome β , and between the predictor and the outcome τ). It was found that α in general would have a lower parameter bias when compared to β and τ . I speculate that this was perhaps due to the nature of complex causal relationship in the model that the lack of estimation precision in the preceding part of the causal relationship would be carried forward to the latter part of the causal relationship. This idea can be further exemplified when comparing the β^W from both the 1-1-1 mediation model and the 2-1-1 mediation model. The precision of β^W in the 1-1-1 mediation model might depend on the precision of α^W that preceded it in the causal system; but the β^W in the 2-1-1 mediation model did not depend on α^W .

4.6 Limitations and Future Directions

The current study only considered equal factor loadings of the indicators which may not be realistic in empirical research. A potential design artefact of using equal factor loadings in simulating the three-form design is the creation of true parallel forms in which all three forms measure the latent construct with the same degree of precision. The impact of the three-form design with items that do not relate equally to the latent factor should be explored via non-equal factor loadings.

Furthermore, the simulation generated the data with strict time-invariant measurement parameters at the population level. However, in empirical there could be possibility of minor to severe measurement non-invariance. The impact of the degree of measurement non-invariance could be explored to investigate the modelling strategies to take into account the presence of measurement non-invariance.

In relations to model parameters, future research may consider the random effects (e.g., random intercepts and slopes) in the model on top of the fixed effects considered in the current simulation study as it is not uncommon for applied research to model and test hypothesis on the random (individual-varying) effects. I expect that an even larger sample size would be required to have a precise estimation of the individual random effects based on the results in Schultzberg and Muthén (2018) when non-informative priors are used. Additional multilevel longitudinal mediation models (e.g., 1-1-2, 2-2-1, 1-2-1, 1-2-2, 2-1-2 models; Preacher et al., 2010) can also be considered in future research. Extension of the mediation models with a moderated mediation process can also be examined.

Lastly, even though the data-fitting model was not the same as the data-generating model but an over-specified model (i.e., additional of covariance of the disturbance in the level-1 model, and intercepts parameters of the latent indicators in the level-2 model; see Figure 4.3.3 and Figure 4.3.4) compared to the data-generating model in Figure 4.3.1 and Figure 4.3.2), the over-specified parameters were unlikely to have a significant effect on the estimation of the other model parameters as evident by the small parameter bias (i.e., the estimates of those over-specified parameters were close

to 0) other than a probable longer computing time for the more complex model due to a larger number of free parameter that needed to be estimated. Descriptive statistics of these over-specified parameters can be found in section D.3.

4.7 Recommendations

Based on the results of this study, I would first suggest applied researchers to apply informative priors (as opposed to non-informative prior used by software defaults) in the estimation of the parameters when possible. This could potentially lower the relative bias, especially at the large effect size conditions, as effect size is not a controllable element in a research design but an expression of the empirical data. Future research should be conducted to evaluate the use of informative priors to support this suggestion. When non-informative prior was used, I would recommend to use a sample size of at least 200 if the level-2 parameters are of interest in order to obtain an acceptable rejection. The results also indicated that measurement occasion of 30 time-points seemed to be sufficient.

Lastly, the study also showed that planned-missing data as implemented using the three-form design provided parameter estimates that were comparable to the full-data conditions, therefore providing support on the use of such design in the intensive longitudinal research as a potential solution to reduce participant fatigue.

Chapter 5

Study 3

Test for Time-Varying Mediation Effect in Intensive Longitudinal Data through Dynamic Structural Equation Modelling

Study 2 investigated the longitudinal mediation models with a critical assumption that the structural path coefficients (i.e., the relationship between variables) are time-invariant. Such assumption may have been an oversimplification of the complex dynamic processes that are inherent in psychological processes.

The time-varying effect model (TVEM) is a type of varying-coefficient model (Hastie & Tibshirani, 1993) that allows variation in the magnitude of association among variables over time (Tan et al., 2012). The Dynamic Structural Equation Modeling (DSEM; Asparouhov et al., 2018) framework for intensive longitudinal data is one of the existing methods that has the flexibility to model and test such dynamic processes. In this context, TVEM can be considered as a special application of DSEM via the cross-classified model.

5.1 Background

Li et al. (2006) argued that relationship between variables may vary over time due to treatment (e.g., intervention programme) or natural progression of time (e.g., ageing). For example, Tan et al. (2012) found that the effect of positive affect on self-

efficacy on smoking abstinence changes over time with a general smaller effect prior to a scheduled smoking-cessation date. A related smoking-cessation intensive longitudinal study by Li et al. (2006) also found a time-varying effect of negative affect on smoking urges where the effect was strongest during the first week of abstinence which then subsided over the week.

The empirical examples above investigated the time-varying direct effects of variables similar to those of a regular linear regression. There is little to no reason to not infer that a mediation model could also have time-varying direct and/or indirect effects. In fact, the specification of time-varying effect in longitudinal mediation model has been a norm in specifying cross-lagged models.

As illustrated in the 4-wave autoregressive mediation model in Figure 5.1.1 [extended from MacKinnon's (2008) 3-wave autoregressive mediation model I], the coefficient of the structural paths between the predictor (X), mediator (M), and outcome (Y) are allowed to vary (i.e., α_1 , α_2 , and α_3 are not constrained to be equal, similarly for the β parameters, and the τ parameters). Hence, MacKinnon's (2008) classical longitudinal mediation model essentially models a time-varying mediation effect. Echoing Collins's (2006) call for the integration of the conceptual model and statistical model in analysing longitudinal data, Huang and Yuan (2017) further argued for a flexible modelling framework that allows for the testing of time-varying mediation effects for modern research.

Current literature on the evaluation of the TVEM focused on the recovery of the functional form of the relationships between variables over time (e.g., Huang & Yuan, 2017; Tan et al., 2012). This was perhaps due to the common implementation of the *non-parametric* spline-based method to estimate the varying effect (e.g., Tan et al., 2012). In contrast, the objective of this study was to investigate the *parametric* modelling of time-varying effect using random effects (i.e., mean and variance of a random variable as parameters) as implemented in the DSEM framework. However, this is not to imply that the DSEM framework does not allow visualisation of the parameter function forms as a function of time. Several simulation studies have showed that the nu-

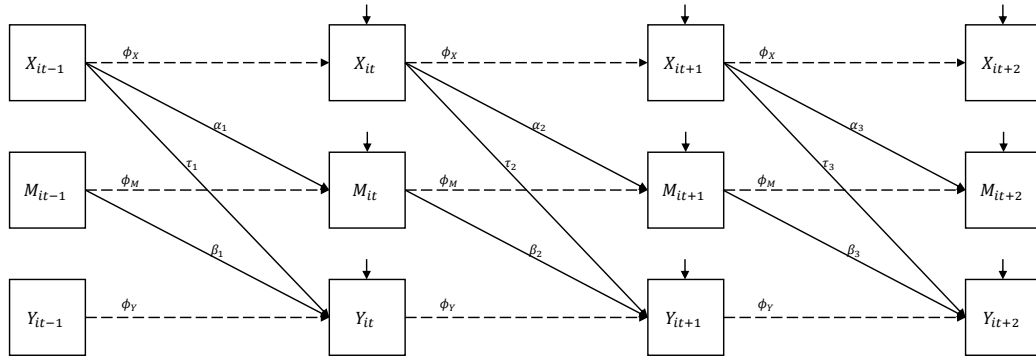


Figure 5.1.1: 4-wave Autoregressive Mediation Model

merical estimates of the random effect (i.e., factor scores) can recover the functional form to a certain extent (e.g., Asparouhov et al., 2018; Lim & Chew, 2019).

One notable limitation of the implementation of TVEM in Mplus v8.3, which this dissertation was largely based on, is that time-varying random slope involving lagged-latent variables cannot be estimated (see Asparouhov et al., 2018). An implication of this software limitation is that measurement model cannot be explicitly specified in TVEM models when time-varying random effects of the lagged latent factors are of interest. Therefore, researchers would have to fall back on using observed variable via scaled scores (e.g., sum, averaged, etc.) of multiple-items measurement to enable the modelling of such effects. Based on the classical test theory (i.e., $\sigma_Y^2 = \sigma_T^2 + \sigma_E^2$), larger measurement error variance would lead to a lower reliability ($\omega = 1 - \frac{\sigma_E^2}{\sigma_Y^2}$). Without the use of a measurement model to dissociate the measurement error variance and the true score variance, relationships between observed variables would be attenuated with a positive relationship between measurement error and degree of attenuation (McDonald, 1999).

5.2 Objectives

In summary, the primary objective of this simulation study was to investigate the recovery of the mean and variance of each random effect of time (i.e., time-varying intercept and slope) in a time-varying effect mediation model under the presence of planned-missing data, with varying degree of effect sizes and measurement reliability.

5.3 Method

5.3.1 Data-generating Models

Due to the constraint of the current implementation of TVEM in Mplus v8.3, variances of random slope involving lagged latent variables cannot be estimated. Therefore, the data-generation and model-fitting processes for this study deviated slightly from that in chapter 4 to reflect this limitation in the analysis of real-world data whilst keeping the general structure of a simple mediation model. The two-step data-generating process is described in the following section.

Data Generation Step 1

As reviewed in chapter 2, implementation of TVEM in Mplus is based on the cross-classified model in which observations (i.e., X_{it} , Y_{it} , and Z_{it}) are nested under level-2 Individual-cluster and Time-cluster (refer to the data-generating model for this study in Figure 5.3.1). At the within-level, the structural disturbances were generated to be independent with unit variance; At the between-time and between-individual levels, the variance of the random effects were also generated to be independent.

As iterated, the time-varying regression slope between X_{it} , Y_{it} , and Z_{it} and their lagged variables were modelled as a combination of fixed (using the mean parameter) and random effects (using the variance parameter) at the between-level in the cross-classified model under the DSEM framework implemented in Mplus. Individual-specific intercepts of the three variables were also simulated by specifying them as ran-

dom effects (using the variance parameter) at the individual-level. The parameters values that were constant across the simulation conditions were expressed below:

Within-level:

$$\begin{aligned}
X_{it} &= \mu_{X \cdot i} + \phi_X * X_{it-1} + \varepsilon_{X \cdot it} \\
M_{it} &= \mu_{M \cdot i} + \phi_M * M_{it-1} + \alpha_t * X_{it-1} + \varepsilon_{M \cdot it} \\
Y_{it} &= \mu_{Y \cdot i} + \phi_Y * Y_{it-1} + \beta_t * M_{it-1} + \tau_t * X_{it-1} + \varepsilon_{Y \cdot it}
\end{aligned} \tag{5.1}$$

where $\phi_X = \phi_M = \phi_Y = 0.2$, and $\sigma_{\varepsilon_X}^2 = \sigma_{\varepsilon_M}^2 = \sigma_{\varepsilon_Y}^2 = 1$

Between Time-level:

$$\begin{aligned}
\alpha_t &= \gamma_\alpha + \xi_{\alpha_t} \\
\beta_t &= \gamma_\beta + \xi_{\beta_t} \\
\tau_t &= \gamma_\tau + \xi_{\tau_t}
\end{aligned} \tag{5.2}$$

Between Individual-level:

$$\begin{aligned}
\mu_{X \cdot i} &= \gamma_X + \xi_{X \cdot i} \\
\mu_{M \cdot i} &= \gamma_M + \xi_{M \cdot i} \\
\mu_{Y \cdot i} &= \gamma_Y + \xi_{Y \cdot i}
\end{aligned} \tag{5.3}$$

where $\gamma_X = \gamma_M = \gamma_Y = 0$, and $\sigma_{\xi_X}^2 = \sigma_{\xi_M}^2 = \sigma_{\xi_Y}^2 = 0.5$

Data Generation Step 2

With X_{it} , Y_{it} , and, Z_{it} simulated from the data-generating model in Step 1, these variables were used to generate $j = 5$ observed indicators each to simulate data collected from a battery of questionnaires similar to chapter 3 and chapter 4 via a measurement model by using X_{it} , Y_{it} , and, Z_{it} as the realisation of the random variable (latent factor)

in Equation 5.4 below:

$$\begin{aligned}
X_{j\cdot it} &= \mu_{X_j} + \lambda_{X_j} * X_{it} + \varepsilon_{X_{j\cdot it}} \\
M_{j\cdot it} &= \mu_{M_j} + \lambda_{M_j} * M_{it} + \varepsilon_{M_{j\cdot it}} \\
Y_{j\cdot it} &= \mu_{Y_j} + \lambda_{Y_j} * Y_{it} + \varepsilon_{Y_{j\cdot it}}
\end{aligned}
\tag{5.4}$$

where $\mu_{X_j} = \mu_{M_j} = \mu_{Y_j} = 0$, and $\lambda_{X_j} = \lambda_{M_j} = \lambda_{Y_j} = 1$

While the intercepts (μ) and factor loadings (λ) parameter values were kept as a constant across all items (j) and time (t), the error variances ($\sigma_{\varepsilon_{X_{j\cdot t}}}^2$, $\sigma_{\varepsilon_{M_{j\cdot t}}}^2$, and $\sigma_{\varepsilon_{Y_{j\cdot t}}}^2$) varied over time depending on two factors: the variance of X_{it} , Y_{it} , and, Z_{it} at time t ($\sigma_{X_t}^2$, $\sigma_{M_t}^2$, and, $\sigma_{Y_t}^2$), and the varying simulation conditions of measurement reliability. In general, the quantification of reliability follows the formula of McDonald's (1999) coefficient ω , where

$$\omega_{\theta_t} = \frac{(\sum_{j=1}^{J=5} \lambda_j)^2 * \sigma_{\theta_t}^2}{(\sum_{j=1}^{J=5} \lambda_j)^2 * \sigma_{\theta_t}^2 + \sum_{j=1}^{J=5} \sigma_{\varepsilon_{j\cdot t}}^2}
\tag{5.5}$$

To solve for the time-specific error variance $\sigma_{\varepsilon_{j\cdot t}}^2$ with the assumption that $\sigma_{\varepsilon_{j\cdot t}}^2 = \sigma_{\varepsilon_{\cdot t}}^2 \forall J$, Equation 5.5 can be arranged as

$$\sigma_{\varepsilon_{j\cdot t}}^2 = \frac{(1 - \omega_{\theta_t}) * (\sum_{j=1}^{J=5} \lambda_j)^2 * \sigma_{\theta_t}^2}{J * \omega_{\theta_t}}
\tag{5.6}$$

With Equation 5.6, the resulting error variances were used to specify a diagonal covariance matrix to simulate $\varepsilon_{X_{j\cdot it}}$, $\varepsilon_{M_{j\cdot it}}$, and $\varepsilon_{Y_{j\cdot it}}$ from a multivariate normal distribution with mean 0 to be used in Equation 5.4 to generate $X_{j\cdot it}$, $M_{j\cdot it}$, and, $Y_{j\cdot it}$ for $j = 1, 2, \dots, 5$ and t depending on the simulation condition as described in the next section.

5.3.2 Simulation Setup

To simulate data to represent real-world observation as close as possible, the sample sizes (N) and measurement occasions (T) considered in the current simulation were $N = 50, 100$, and, 200 , and $T = 15, 30, 60$, and 120 , respectively. The population values

of the mean parameter of the random slope (fixed effect; FE) were chosen to represent a relative smaller and larger effect size $\gamma = 0.3$ and 0.6 (e.g., Krull & MacKinnon, 2001), and population value of the variance parameter of the random slope (random effect; RE) were $\sigma_{\xi}^2 = 0.16$ and 0.64 respectively. The time-invariant measurement reliability was generated as $\omega_{\theta} = 0.60$ and 0.80 .

Similar to both Study 1 and Study 2, missing data was simulated using a 3-form design with varying-form distribution pattern (see Table 3.3 in subsection 3.2.1 for an illustration). With reference to the data-generating model, each of the three "factor" was simulated to be measured by 5 items at each time point, 3 levels of missing data percentages were considered, $PMD = 0\%$ (i.e. full data), 20% (i.e. 3 out of 15 items omitted), and 40% (i.e. 6 out of 15 items omitted). Please refer to Study 2 (Table 4.1 and Table 4.2 described in subsection 4.3.2) on the procedure for simulating the three-form design.

500 replications were done for each combination of the levels of the independent variables described above using Mplus for data generation Step 1, R for data generation Step 2 (see section E.1), and Mplus for model fitting (see section E.2). Two chains with a minimum of 2500 iterations and maximum of 4000 iterations were used for the estimation.

Fitted Model

Recalling the limitation of the current implementation of TVEM in Mplus that time-varying effects involving latent lagged variables cannot be modelled. Therefore, prior to fitting the simulated data to the model in figure 5.3.2, the observed responses of the items (X_{j-it} , M_{j-it} , and M_{j-it}) were combined to obtain a composite score (X_{it}^* , M_{it}^* , and

Y_{it}^*) for each "factor" following

$$\begin{aligned} X_{it}^* &= \frac{\sum_j^J X_{j \cdot it}}{J} \\ M_{it}^* &= \frac{\sum_j^J M_{j \cdot it}}{J} \\ Y_{it}^* &= \frac{\sum_j^J Y_{j \cdot it}}{J} \end{aligned} \quad (5.7)$$

Note that J in Equation 5.7 may differ depending on the simulation condition for missing data. In condition $M = 0\%$, $J = 5$, while in condition $M = 20\%$, $J = 4$, and in condition $M = 40\%$, $J = 3$ at each t^{th} measurement occasion. This approach was used to simulate a commonly applied method to calculate averaged scores by only using observed indicators.

Contrasting it to the data-generating model in Figure 5.3.1, the structural disturbance in the data-fitting model in Figure 5.3.2 were modelled to covary as the default setting in Mplus. Other than that, variance of random intercepts (ξ_{X_i} , ξ_{M_i} , and ξ_{Y_i}) were modelled at the between-time level and variance of random slopes (ξ_{α_i} , ξ_{β_i} , and ξ_{τ_i}) were also modelled at the between-individual level which both were *absent* from the data-generating model to reflect a realistic decision in the modelling process that researchers would likely take to test the presence of time-varying and individual-varying effects.

5.3.3 Evaluation Measures

The evaluation measures used in this study were similar to those in Study 2. The following section was largely reproduced from Study 2 for ease of reading, with some changes in the rejection subsection where an additional ROPE was defined for the variance parameter of the random effect.

Relative Bias

Relative bias (RB) is defined as the difference between point-estimate ($\hat{\theta}$) and the true value (θ) of the parameter divide by the true value,

$$RB = \left(\frac{\hat{\theta} - \theta}{\theta} \right) \quad (5.8)$$

A positive value represents an over-estimation and a negative value represents an under-estimation, relative to the true value. For example, an RB value of 0.02 represents a *2% over-estimation* relative to the true value; an RB value of -0.02 represents a *2% under-estimation* relative to the true value. An *absolute* RB value of less than 5% indicates trivial bias, values between 5% and 10% indicate moderate bias, while values greater than 10% indicate substantial bias (e.g., Flora & Curran, 2004). The median of the posterior distribution was used as the point estimate as per default in Mplus. Readers who are not familiar with the concept of the parameter posterior distribution may refer to Appendix A. Note that the *RB* is undefined for parameters that have a population value of 0 (e.g., random intercept at the level-2 Time cluster); therefore *RB* was not reported for these parameters.

Coverage

Coverage is defined as the average number of replications with the highest density interval (HDI) containing the true population parameter value,

$$Coverage = \frac{\text{number of HDI that contains } \theta}{\text{number of replications}} \quad (5.9)$$

Coverage ranges from 0 to 1, with 0 representing none of the HDIs across the replications contain the true value, and a value of 1 represents all HDIs across to the replications contain the true value. The 90% HDI was used for the computation as recommended by Kruschke (2014). For the purpose of this study, a coverage value of 0.87 and above is considered good coverage, adapting the criteria used in Schultzberg and Muthén (2018). Readers who are not familiar with the concept of HDI may refer to

Appendix A. Coverage was not reported for parameters which population value is 0 as the coverage index for these parameters conveys similar information as the rejection index as described in the next section and rejection is deemed more informative.

Rejection

Rejection is defined as the average number of replications with HDI that *does not* contain the Region of Practical Equivalence (ROPE; see Appendix A for more details),

$$Rejection = \frac{\text{number of HDI that do not contain ROPE}}{\text{number of replications}} \quad (5.10)$$

The ROPE for the random effect mean parameters of interest for this study was specified as [-0.05, 0.05] as suggested in Kruschke (2018); while the ROPE for the random effect variance parameters was truncated as [0, 0.05], if not stated otherwise. Rejection ranges from 0 to 1, with 0 representing all of the 90% HDIs across the replications contain the ROPE, and a value of 1 represents none of the 90% HDIs across to the replications do not contain the ROPE. Readers who are not familiar with the use of HDI and ROPE as an alternative to hypothesis testing may refer to Appendix A.

If the population value is not 0 of a parameter, a value of 0.80 and above is considered an acceptable rejection for the purpose of this study (i.e., 400 out of 500 replications had corresponding 90% HDIs that *correctly* excluded the ROPE). If the population value is 0, a value of 0.20 and below is considered an acceptable rejection for the purpose of this study (i.e., 100 out of 500 replications had corresponding 90% HDIs that *incorrectly* excluded the ROPE).

Convergence

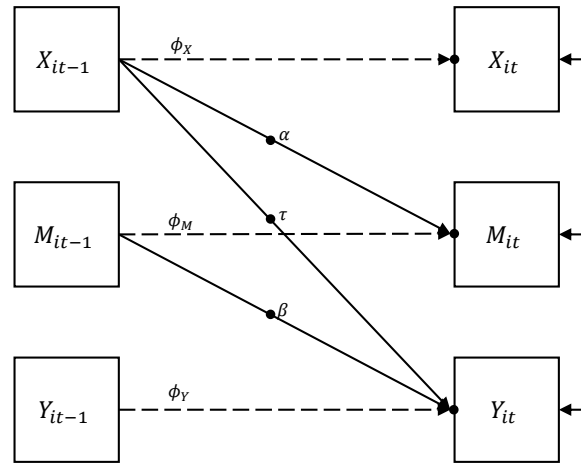
Convergence of the Gibbs Sampling MCMC for parameters in each replication was assessed using the Potential Scale Reduction (PSR) factor. Only replications that successfully converged were included in the analysis and replications that failed to converge were not replaced with new replications. Readers who are not familiar with the PSR factor may refer to Appendix A.

5.4 Results

The results below were organised by the type of parameters (i.e., slope or intercept) and at their corresponding level in the model (i.e., between-time or between-individual).

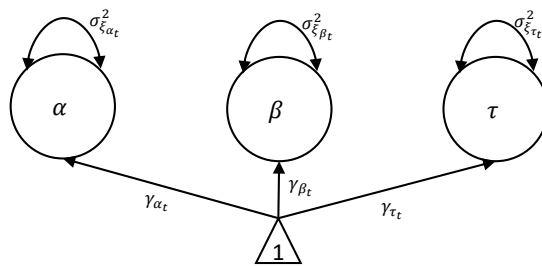
5.4.1 Convergence

Table 5.1 suggested that the cross-classified model might suffer from convergence problem at certain conditions, especially at the larger fixed effect size ($FE = 0.60$) condition. For the larger fixed effect size condition, the results also suggested that a larger sample size (e.g., $N = 200$) might not improve the convergence rate; in contrast, a larger measurement occasion ($T = 60$ and 120) might lead to higher convergence rate for the larger random effect size ($RE = 0.64$) condition. The $PMD = 40\%$ condition seemed to have the lowest convergence rate in most combination of simulation conditions. The convergence rate were consistently higher at the $FE = 0.30$ and $RE = 0.16$ conditions. The convergence rate between the $\omega = 0.60$ and the $\omega = 0.80$ were generally similar.



Within

Between Time



Between Individual

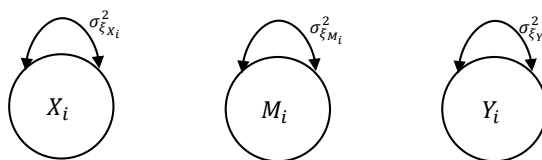
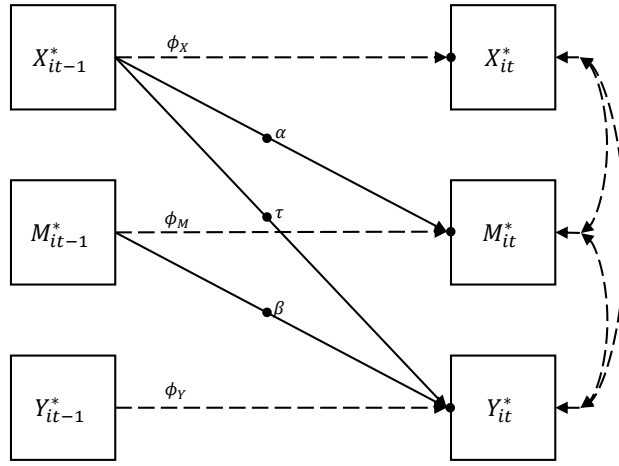
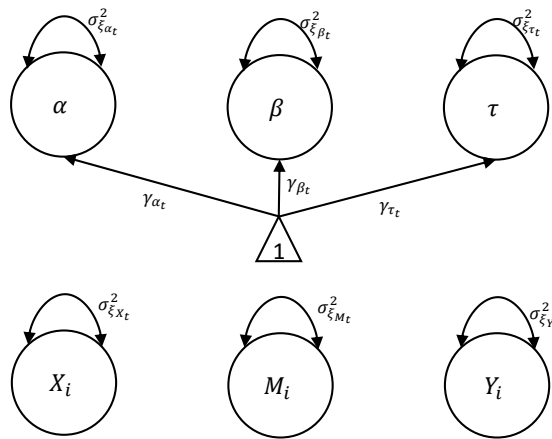


Figure 5.3.1: Data-Generating TVEM



Within

Between Time



Between Individual

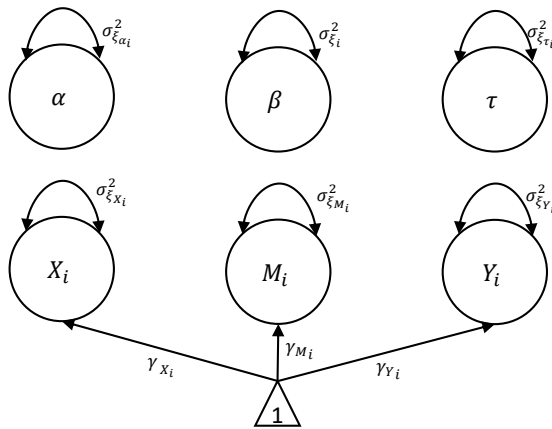


Figure 5.3.2: Fitted TVEM

Table 5.1: Model Convergence Rate for 500 Replications

FE	T	PMD	RE = 0.16			RE = 0.64		
			50	100	200	50	100	200
$\omega = 0.60$								
0.3	15	0%	0.988	0.984	0.904	0.910	0.912	0.778
		20%	0.998	0.994	0.946	0.920	0.944	0.842
		40%	0.978	0.946	0.824	0.908	0.780	0.626
	30	0%	0.984	0.996	0.892	0.942	0.964	0.804
		20%	0.994	0.996	0.902	0.950	0.980	0.870
		40%	0.992	0.964	0.798	0.940	0.850	0.686
	60	0%	0.990	0.996	0.966	0.972	0.986	0.952
		20%	0.992	0.998	0.964	0.968	0.990	0.966
		40%	0.992	0.954	0.796	0.912	0.852	0.664
	120	0%	0.988	1.000	0.994	0.988	0.994	1.000
		20%	0.990	1.000	0.998	0.984	0.992	1.000
		40%	0.988	0.986	0.838	0.956	0.906	0.836
0.6	15	0%	0.452	0.872	0.750	0.790	0.836	0.716
		20%	0.906	0.928	0.908	0.906	0.910	0.800
		40%	0.396	0.634	0.574	0.692	0.628	0.528
	30	0%	0.416	0.872	0.750	0.860	0.904	0.802
		20%	0.526	0.930	0.884	0.924	0.966	0.856
		40%	0.488	0.746	0.772	0.654	0.744	0.600
	60	0%	0.686	0.710	0.802	0.950	0.956	0.930
		20%	0.938	0.974	0.924	0.958	0.992	0.930
		40%	0.560	0.750	0.682	0.778	0.680	0.482
	120	0%	0.136	0.698	0.726	0.982	0.998	0.970
		20%	0.976	0.814	0.702	0.970	0.994	0.972
		40%	0.012	0.812	0.598	0.610	0.688	0.552
$\omega = 0.80$								
0.3	15	0%	0.990	0.990	0.878	0.910	0.922	0.740
		20%	0.994	0.992	0.916	0.910	0.930	0.804
		40%	0.992	0.982	0.854	0.920	0.882	0.686
	30	0%	0.990	0.998	0.884	0.958	0.970	0.798
		20%	0.988	0.986	0.892	0.946	0.980	0.840
		40%	0.988	0.978	0.782	0.956	0.930	0.746
	60	0%	0.992	0.998	0.966	0.976	0.990	0.942
		20%	0.988	1.000	0.966	0.976	0.992	0.968
		40%	0.986	0.988	0.838	0.950	0.962	0.894
	120	0%	0.988	1.000	0.992	0.704	0.994	1.000
		20%	0.986	1.000	0.996	0.988	1.000	1.000
		40%	0.984	0.998	0.904	0.986	0.994	0.974
0.6	15	0%	0.578	0.936	0.742	0.828	0.856	0.660
		20%	0.852	0.968	0.848	0.886	0.922	0.734
		40%	0.522	0.908	0.630	0.798	0.798	0.568
	30	0%	0.468	0.900	0.780	0.874	0.918	0.790
		20%	0.608	0.946	0.854	0.912	0.960	0.820
		40%	0.402	0.854	0.728	0.796	0.832	0.640
	60	0%	0.746	0.808	0.792	0.960	0.966	0.920
		20%	0.944	0.914	0.864	0.960	0.970	0.926
		40%	0.550	0.822	0.694	0.892	0.862	0.672
	120	0%	0.206	0.738	0.706	0.142	0.998	0.966
		20%	0.864	0.926	0.876	0.982	0.992	0.974
		40%	0.016	0.746	0.708	0.912	0.936	0.808

Note: FE = Fixed Effect of Between-Time Random Slope; RE = Random Effect of Between-Time Random Slope; N = Sample Size; T = measurement occasions; PMD = Planned-Missing Data Percentage; ω = reliability. The values represent the proportion of converged replications out of the 500 total replications for each combination of conditions (e.g., 1.000 = all 500 replications converged successfully; 0.800 = 400 out of 500 replications converged successfully). Values smaller than 0.80 were in bold.

5.4.2 Random Slope at Between-Time Level

Fixed Effect ($\gamma_{\alpha_t}, \gamma_{\beta_t}, \gamma_{\tau_t}$)

Table 5.2, Table 5.3, and Table 5.3 contained the average parameter estimate over successful replication for the fixed effect of the random slopes. These parameters represented the mean of the random variables at the between-time level in Figure 5.3.2). The values in the parenthesis contained the average of the standard deviation of the parameter posterior distribution over successful replications.

From the tables, a consistent pattern could be observed with regards to T (measurement occasions) and its relation with the parameter point-estimate and precision (standard deviation of posterior distribution): With a larger T , the point-estimate seemed to be closer to the population value (see *FE* column) and the standard deviation of posterior distribution was smaller.

Relative Bias The relative bias of the three parameters of interest were presented in the following tables respectively: Table 5.5, Table 5.6, and Table 5.7. The results concurred with the observation that for all parameters, an increasing measurement occasion T was associated with a decreasing relative bias for the parameters. However, only the complete-data ($PMD = 0\%$) condition at $T = 60$ and 120 had an acceptable relative bias (except for γ_{β_t} at $FE = 0.60$ which largely had an unacceptable relative bias). All the simulation conditions of $PMD = 20\%$ and 40% resulted in unacceptable relative bias, and the magnitude and direction of the bias depended on the specific parameter; however, in general the $PMD = 20\%$ conditions had a lower bias than $PMD = 40\%$. Reliability (ω) also seemed to play a role in the conditions of $PMD = 20\%$ and 40% in that $\omega = 0.80$ generally had a lower bias than $\omega = 0.60$. Sample size (N) did not seem to have an effect on the relative bias.

Coverage Similar to the relative bias results, the $PMD = 20\%$ and 40% conditions resulted in an unacceptable low coverage in general. Similarly, the coverage value of the $PMD = 20\%$ and 40% conditions was dependent on the reliability (ω) with a gen-

eral lower coverage at $\omega = 0.60$ compared to $\omega = 0.80$. Overall, the coverage was only acceptable at $PMD = 0\%$ regardless of the other experimental factors considered in the simulation (except for γ_{β_t} at $FE = 0.60$ which did not reach the acceptable coverage).

On the other hand, there were no notable difference in coverage of the parameters between the different levels of sample size (N) and levels of measurement occasions (T) considered in this simulation. The coverage results can be found in Table 5.8, Table 5.9, and Table 5.10.

Rejection Similar to the relative bias results, an increment in measurement occasions T was related to the increment in rejection (i.e., correct rejection of the null value) in general. Furthermore, the $FE = 0.60$ conditions tended to have a higher rejection than the $FE = 0.30$ conditions. Based on the values in Table 5.11, Table 5.9, and Table 5.10, sample size N and reliability ω did not seem to have a notable effect on the rejection. The effect of PMD largely depended on the magnitude of relative bias and the spread of the posterior distribution (i.e., precision) of the parameter (e.g., a biased parameter with a wide HDI may still contain the ROPE; but a biased parameter with a smaller HDI may not contain the ROPE). Nevertheless, for the parameters in conditions which had acceptable relative bias (i.e., $T = 60$ and 120 , and $PMD = 0\%$), the rejection for the parameters were all above the acceptable level of 0.80.

Random Effect ($\sigma_{\xi_{\alpha_t}}^2, \sigma_{\xi_{\beta_t}}^2, \sigma_{\xi_{\tau}}^2$)

Table 5.14, Table 5.15, and Table 5.15 contained the average parameter estimate over successful replication for the random effect of the random slopes (These parameters represented the *variance* of the random variables at the between-time level in Figure 5.3.2). The values in the parenthesis contained the average of the standard deviation of the parameter posterior distribution over successful replications.

From the tables, a consistent pattern could be observed with regards to T (measurement occasions) and its relation with the parameter point-estimate and posterior standard deviation: With a larger T , the point-estimate seemed to be closer to the popula-

Table 5.2: Descriptive Statistics for Fixed Effect of Random Slope α at Between-Time Level

FE	T	PMD	$\omega = 0.60$			$\omega = 0.80$			
			50	N 100	200	50	N 100	200	
0.3	15	0%	0.268 (0.182)	0.266 (0.177)	0.282 (0.176)	γ_{α}	0.271 (0.181)	0.268 (0.177)	0.283 (0.176)
		20%	0.065 (0.138)	0.068 (0.130)	0.075 (0.130)		0.179 (0.160)	0.178 (0.154)	0.191 (0.154)
		40%	0.537 (0.116)	0.531 (0.111)	0.543 (0.104)		0.415 (0.148)	0.409 (0.143)	0.424 (0.139)
	30	0%	0.289 (0.122)	0.279 (0.116)	0.282 (0.116)		0.290 (0.122)	0.279 (0.116)	0.282 (0.116)
		20%	0.093 (0.092)	0.087 (0.086)	0.089 (0.085)		0.198 (0.107)	0.191 (0.101)	0.193 (0.102)
		40%	0.555 (0.077)	0.548 (0.071)	0.548 (0.069)		0.437 (0.098)	0.425 (0.093)	0.427 (0.093)
	60	0%	0.292 (0.084)	0.297 (0.081)	0.296 (0.082)		0.293 (0.084)	0.297 (0.081)	0.296 (0.082)
		20%	0.105 (0.066)	0.111 (0.060)	0.107 (0.059)		0.204 (0.075)	0.208 (0.071)	0.206 (0.071)
		40%	0.551 (0.055)	0.550 (0.050)	0.552 (0.048)		0.437 (0.069)	0.440 (0.065)	0.441 (0.065)
	120	0%	0.299 (0.058)	0.294 (0.057)	0.302 (0.056)		0.300 (0.055)	0.294 (0.057)	0.302 (0.056)
		20%	0.118 (0.048)	0.113 (0.044)	0.119 (0.041)		0.213 (0.052)	0.208 (0.051)	0.215 (0.049)
		40%	0.551 (0.041)	0.545 (0.037)	0.551 (0.035)		0.444 (0.049)	0.438 (0.047)	0.444 (0.045)
0.6	15	0%	0.551 (0.203)	0.527 (0.187)	0.560 (0.182)	0.560 (0.197)	0.532 (0.186)	0.564 (0.179)	
		20%	0.214 (0.139)	0.206 (0.129)	0.211 (0.122)	0.386 (0.162)	0.373 (0.155)	0.393 (0.148)	
		40%	0.762 (0.112)	-0.111 (0.287)	-1.280 (0.524)	0.675 (0.149)	0.645 (0.146)	0.676 (0.133)	
	30	0%	0.587 (0.138)	0.564 (0.119)	0.579 (0.121)	0.590 (0.136)	0.563 (0.119)	0.579 (0.120)	
		20%	0.245 (0.097)	0.242 (0.083)	0.243 (0.080)	0.414 (0.112)	0.403 (0.099)	0.406 (0.098)	
		40%	0.469 (0.148)	0.376 (0.153)	0.488 (0.123)	0.711 (0.101)	0.680 (0.091)	0.700 (0.086)	
	60	0%	0.588 (0.088)	0.584 (0.086)	0.585 (0.083)	0.590 (0.087)	0.583 (0.085)	0.585 (0.083)	
		20%	0.273 (0.067)	0.275 (0.059)	0.270 (0.056)	0.427 (0.073)	0.421 (0.070)	0.421 (0.068)	
		40%	0.664 (0.080)	0.555 (0.097)	0.681 (0.065)	0.710 (0.067)	0.698 (0.062)	0.703 (0.060)	
	120	0%	0.593 (0.072)	0.589 (0.061)	0.602 (0.059)	0.593 (0.055)	0.589 (0.061)	0.602 (0.059)	
		20%	0.288 (0.051)	0.282 (0.045)	0.284 (0.041)	0.432 (0.054)	0.430 (0.050)	0.436 (0.048)	
		40%	0.792 (0.043)	0.759 (0.037)	0.777 (0.031)	0.725 (0.055)	0.707 (0.045)	0.717 (0.042)	

Note: *FE* = Fixed Effect; *N* = Sample Size; *T* = Measurement Occasions; *PMD* = Planned-Missing Data Percentage; ω = Reliability. The values outside the brackets represent the average point-estimate of the parameter across the successful replications. The values enclosed in the brackets represent the average standard deviation of the posterior distribution of the parameter across the successful replications.

tion value (see the *RE* column) and the standard deviation of the posterior distribution was smaller. This pattern was similar to that of the fixed effect of the random slope in the previous section.

Relative Bias Based on Table 5.17, Table 5.18, and Table 5.19, as observed in the descriptive statistics tables, the relative bias decreased with an increase in *T*, but the *T* = 120 combined with the *PMD* = 0% seemed to be the only conditions that reliably obtained an acceptable relative bias. In general, the *PMD* = 20% and 40% substantially underestimated the parameter, with $\omega = 0.60$ producing larger bias than the $\omega = 0.80$ conditions. Sample size *N* and effect size *RE* did not seem to have an effect on the relative bias. These observed patterns were similar across the three parameters of interest.

Coverage The coverage of the three parameters are presented in Table 5.20, Table 5.21, and Table 5.21. The results indicated that the coverage were above the accept-

Table 5.3: Descriptive Statistics for Fixed Effect of Random Slope β at Between-Time Level

FE	T	PMD	$\omega = 0.60$			$\omega = 0.80$			
			50	N 100	200	50	N 100	200	
0.3	15	0%	0.256 (0.188)	0.271 (0.184)	0.281 (0.178)	γ_{β_r}	0.261 (0.187)	0.274 (0.184)	0.283 (0.177)
		20%	0.192 (0.153)	0.201 (0.150)	0.207 (0.144)		0.219 (0.171)	0.229 (0.167)	0.236 (0.161)
		40%	0.472 (0.141)	0.484 (0.131)	0.285 (0.167)		0.381 (0.163)	0.392 (0.156)	0.401 (0.149)
	30	0%	0.283 (0.121)	0.282 (0.120)	0.283 (0.114)		0.284 (0.121)	0.284 (0.120)	0.283 (0.114)
		20%	0.217 (0.098)	0.214 (0.097)	0.215 (0.092)		0.241 (0.110)	0.241 (0.109)	0.241 (0.104)
		40%	0.504 (0.090)	0.509 (0.085)	0.480 (0.087)		0.411 (0.105)	0.410 (0.102)	0.412 (0.098)
	60	0%	0.296 (0.085)	0.298 (0.080)	0.293 (0.081)		0.296 (0.085)	0.298 (0.080)	0.294 (0.081)
		20%	0.230 (0.069)	0.232 (0.065)	0.229 (0.065)		0.255 (0.078)	0.256 (0.073)	0.253 (0.074)
		40%	0.518 (0.065)	0.516 (0.058)	0.515 (0.056)		0.421 (0.074)	0.424 (0.069)	0.421 (0.070)
	120	0%	0.294 (0.056)	0.294 (0.058)	0.300 (0.057)		0.295 (0.053)	0.294 (0.058)	0.300 (0.057)
		20%	0.232 (0.046)	0.232 (0.046)	0.237 (0.046)		0.255 (0.051)	0.255 (0.052)	0.260 (0.052)
		40%	0.517 (0.044)	0.514 (0.043)	0.518 (0.042)		0.423 (0.050)	0.422 (0.050)	0.427 (0.050)
0.6	15	0%	-5.430 (1.400)	-4.820 (1.260)	-25.100 (5.260)	-0.871 (0.479)	-1.890 (0.669)	-12.300 (2.730)	
		20%	0.352 (0.168)	0.432 (0.149)	0.245 (0.181)	0.393 (0.187)	0.264 (0.210)	-1.200 (0.498)	
		40%	-14.300 (3.170)	-13.400 (3.000)	-47.000 (9.570)	-3.150 (0.930)	-4.100 (1.120)	-21.100 (4.470)	
	30	0%	-4.940 (1.220)	-14.800 (3.300)	-15.300 (3.310)	-2.330 (0.704)	-11.100 (2.540)	-10.700 (2.380)	
		20%	0.458 (0.104)	0.135 (0.164)	0.355 (0.113)	0.428 (0.128)	-1.680 (0.567)	-0.432 (0.294)	
		40%	-18.200 (3.870)	-24.800 (5.420)	-29.800 (6.210)	-8.040 (1.860)	-17.400 (3.880)	-19.900 (4.260)	
	60	0%	-0.214 (0.258)	-7.140 (1.660)	-4.540 (1.150)	0.218 (0.166)	-5.670 (1.380)	-2.950 (0.822)	
		20%	0.482 (0.067)	0.485 (0.062)	0.459 (0.068)	0.519 (0.076)	0.064 (0.169)	0.402 (0.099)	
		40%	-6.130 (1.530)	-13.000 (2.860)	-13.600 (3.010)	-1.070 (0.455)	-9.740 (2.230)	-7.870 (1.850)	
	120	0%	0.582 (0.070)	-1.240 (0.469)	-1.850 (0.615)	0.561 (0.054)	-0.810 (0.373)	-1.340 (0.500)	
		20%	0.489 (0.044)	0.493 (0.046)	0.491 (0.046)	0.521 (0.051)	0.517 (0.055)	0.512 (0.055)	
		40%	0.464 (0.119)	-5.190 (1.310)	-5.510 (1.400)	0.590 (0.089)	-3.510 (0.977)	-4.330 (1.180)	

Note: FE = Fixed Effect; N = Sample Size; T = Measurement Occasions; PMD = Planned-Missing Data Percentage; ω = Reliability. The values outside the brackets represent the average point-estimate of the parameter across the successful replications. The values enclosed in the brackets represent the average standard deviation of the posterior distribution of the parameter across the successful replications.

able rate only at the $PMD = 0\%$ conditions in general. The coverage decreased with under the conditions of $PMD = 20\%$ and 40% . However, under the conditions of $PMD = 20\%$ and 40% , $\omega = 0.80$ produced a higher coverage than $\omega = 0.60$. With an increase in T there seemed to be a decrease in coverage, this was perhaps due to its relationship with the spread of the posterior distribution (i.e., a smaller T had a wider HDI compared to a smaller T). Sample size N and effect size RE did not seem to have an effect on the coverage.

Rejection The effect of RE can be observed in Table 5.23, Table 5.24, and Table 5.24. At $RE = 0.64$, the rejection of the parameter (i.e., rate of correct rejection of null value) were generally close to 1.00 at all combination of experimental factors considered in the simulation. At $RE = 0.16$, rejection was generally above the acceptable threshold with $T = 30$ and above paired with $PMD = 0\%$. Reliability ω also seemed to have an effect on rejection with $\omega = 0.80$ resulting in higher rejection for the parameters than ω

Table 5.4: Descriptive Statistics for Fixed Effect of Random Slope τ at Between-Time Level

FE	T	PMD	$\omega = 0.60$			$\omega = 0.80$			
			50	N 100	200	50	N 100	200	
0.3	15	0%	0.270 (0.188)	0.266 (0.188)	0.270 (0.177)	γ_{τ}	0.273 (0.188)	0.271 (0.188)	0.272 (0.176)
		20%	0.491 (0.145)	0.484 (0.144)	0.490 (0.136)		0.379 (0.166)	0.375 (0.166)	0.375 (0.157)
		40%	0.081 (0.126)	0.075 (0.121)	0.081 (0.116)		0.165 (0.153)	0.160 (0.152)	0.167 (0.143)
	30	0%	0.278 (0.126)	0.277 (0.124)	0.289 (0.116)		0.277 (0.127)	0.278 (0.124)	0.289 (0.116)
		20%	0.507 (0.098)	0.505 (0.095)	0.513 (0.088)		0.390 (0.112)	0.391 (0.110)	0.400 (0.103)
		40%	0.100 (0.084)	0.099 (0.080)	0.105 (0.074)		0.175 (0.104)	0.175 (0.100)	0.183 (0.095)
	60	0%	0.290 (0.084)	0.293 (0.081)	0.290 (0.080)		0.291 (0.084)	0.293 (0.081)	0.290 (0.080)
		20%	0.516 (0.066)	0.516 (0.062)	0.515 (0.060)		0.404 (0.075)	0.405 (0.072)	0.403 (0.070)
		40%	0.121 (0.056)	0.124 (0.052)	0.118 (0.050)		0.192 (0.069)	0.193 (0.066)	0.188 (0.065)
	120	0%	0.299 (0.057)	0.292 (0.058)	0.296 (0.056)		0.298 (0.054)	0.292 (0.057)	0.296 (0.056)
		20%	0.516 (0.046)	0.511 (0.045)	0.514 (0.043)		0.409 (0.051)	0.403 (0.051)	0.406 (0.050)
		40%	0.134 (0.039)	0.130 (0.038)	0.132 (0.036)		0.200 (0.047)	0.196 (0.047)	0.197 (0.046)
0.6	15	0%	-0.067 (0.335)	-0.238 (0.346)	-0.740 (0.437)	0.356 (0.240)	0.377 (0.225)	0.345 (0.219)	
		20%	0.445 (0.209)	0.260 (0.239)	0.211 (0.238)	0.290 (0.242)	0.377 (0.222)	0.331 (0.216)	
		40%	0.224 (0.131)	0.233 (0.122)	0.247 (0.111)	0.355 (0.160)	0.349 (0.150)	0.370 (0.138)	
	30	0%	0.335 (0.184)	0.552 (0.127)	0.292 (0.177)	0.454 (0.160)	0.555 (0.127)	0.482 (0.137)	
		20%	-0.105 (0.284)	0.414 (0.168)	-0.404 (0.331)	0.376 (0.176)	0.616 (0.120)	0.308 (0.177)	
		40%	0.276 (0.083)	0.272 (0.076)	0.286 (0.067)	0.384 (0.108)	0.385 (0.097)	0.398 (0.087)	
	60	0%	0.581 (0.089)	0.583 (0.085)	0.590 (0.082)	0.582 (0.088)	0.582 (0.084)	0.591 (0.083)	
		20%	0.620 (0.108)	0.600 (0.107)	0.703 (0.080)	0.705 (0.073)	0.705 (0.070)	0.675 (0.075)	
		40%	0.308 (0.056)	0.312 (0.049)	0.312 (0.044)	0.413 (0.071)	0.416 (0.063)	0.422 (0.061)	
	120	0%	0.595 (0.070)	0.594 (0.061)	0.597 (0.059)	0.588 (0.054)	0.595 (0.061)	0.597 (0.060)	
		20%	0.817 (0.043)	0.378 (0.165)	0.789 (0.049)	0.713 (0.050)	0.671 (0.061)	0.717 (0.048)	
		40%	0.315 (0.046)	0.331 (0.036)	0.332 (0.034)	0.414 (0.056)	0.430 (0.047)	0.432 (0.044)	

Note: FE = Fixed Effect; N = Sample Size; T = Measurement Occasions; PMD = Planned-Missing Data Percentage; ω = Reliability. The values outside the brackets represent the average point-estimate of the parameter across the successful replications. The values enclosed in the brackets represent the average standard deviation of the posterior distribution of the parameter across the successful replications.

= 0.60. Sample size N did not seem to have an effect on rejection.

Table 5.5: Relative Bias of the Fixed Effect of Random Slope α at Between-Time Level

FE	T	PMD	$\omega = 0.60$			$\omega = 0.80$		
			50	N 100	200	50	N 100	200
γ_{α_t}								
0.3	15	0%	-0.107	-0.113	-0.060	-0.098	-0.108	-0.057
		20%	-0.782	-0.773	-0.751	-0.403	-0.407	-0.363
		40%	0.788	0.770	0.811	0.384	0.365	0.412
	30	0%	-0.038	-0.070	-0.059	-0.035	-0.070	-0.058
		20%	-0.690	-0.708	-0.703	-0.340	-0.364	-0.356
		40%	0.851	0.827	0.826	0.458	0.418	0.423
	60	0%	-0.025	-0.010	-0.013	-0.023	-0.011	-0.014
		20%	-0.651	-0.630	-0.645	-0.321	-0.305	-0.313
		40%	0.837	0.835	0.841	0.457	0.468	0.471
	120	0%	-0.003	-0.018	0.007	0.001	-0.019	0.005
		20%	-0.606	-0.622	-0.603	-0.291	-0.306	-0.285
		40%	0.837	0.816	0.836	0.479	0.459	0.482
0.6	15	0%	-0.081	-0.121	-0.066	-0.066	-0.114	-0.060
		20%	-0.644	-0.657	-0.648	-0.356	-0.378	-0.345
		40%	0.270	-1.180	-3.140	0.125	0.075	0.127
	30	0%	-0.021	-0.059	-0.035	-0.017	-0.062	-0.034
		20%	-0.592	-0.596	-0.595	-0.309	-0.328	-0.323
		40%	-0.219	-0.373	-0.187	0.185	0.134	0.167
	60	0%	-0.020	-0.027	-0.025	-0.016	-0.028	-0.025
		20%	-0.545	-0.542	-0.550	-0.288	-0.298	-0.298
		40%	0.106	-0.075	0.136	0.183	0.164	0.172
	120	0%	-0.011	-0.018	0.003	-0.012	-0.018	0.003
		20%	-0.520	-0.530	-0.527	-0.279	-0.283	-0.273
		40%	0.320	0.265	0.295	0.208	0.178	0.196

Note: FE = Fixed Effect; N = Sample Size; T = Measurement Occasions; PMD = Planned-Missing Data Percentage; ω = Reliability. The values represent mean parameter relative bias averaged across successful replications. Values that were not within the acceptable [-0.05 and 0.05] bound were in bold.

Table 5.6: Relative Bias of the Fixed Effect of Random Slope β at Between-Time Level

FE	T	PMD	$\omega = 0.60$			γ_{β_i}	$\omega = 0.80$		
			50	N 100	200		50	N 100	200
0.3	15	0%	-0.145	-0.097	-0.063		-0.129	-0.087	-0.057
		20%	-0.361	-0.332	-0.309		-0.269	-0.235	-0.212
		40%	0.573	0.613	-0.049		0.269	0.307	0.336
	30	0%	-0.057	-0.059	-0.056		-0.055	-0.053	-0.057
		20%	-0.278	-0.285	-0.284		-0.197	-0.198	-0.196
		40%	0.681	0.697	0.600		0.369	0.368	0.372
	60	0%	-0.014	-0.007	-0.022		-0.014	-0.008	-0.022
		20%	-0.235	-0.228	-0.238		-0.150	-0.146	-0.157
		40%	0.725	0.721	0.717		0.404	0.415	0.405
	120	0%	-0.019	-0.020	0.001		-0.016	-0.020	0.001
		20%	-0.226	-0.226	-0.211		-0.149	-0.150	-0.133
		40%	0.724	0.714	0.727		0.411	0.405	0.422
0.6	15	0%	-10.000	-9.020	-42.800	-2.450	-4.150	-21.500	
		20%	-0.413	-0.281	-0.592	-0.345	-0.560	-3.000	
		40%	-24.900	-23.400	-79.400	-6.260	-7.830	-36.200	
	30	0%	-9.230	-25.700	-26.600	-4.890	-19.400	-18.800	
		20%	-0.236	-0.775	-0.408	-0.287	-3.800	-1.720	
		40%	-31.300	-42.400	-50.600	-14.400	-30.000	-34.200	
	60	0%	-1.360	-12.900	-8.570	-0.637	-10.400	-5.920	
		20%	-0.196	-0.192	-0.235	-0.135	-0.893	-0.330	
		40%	-11.200	-22.600	-23.700	-2.780	-17.200	-14.100	
	120	0%	-0.029	-3.060	-4.080	-0.064	-2.350	-3.230	
		20%	-0.186	-0.178	-0.181	-0.131	-0.138	-0.146	
		40%	-0.227	-9.650	-10.200	-0.017	-6.840	-8.220	

Note: FE = Fixed Effect; N = Sample Size; T = Measurement Occasions; PMD = Planned-Missing Data Percentage; ω = Reliability. The values represent mean parameter relative bias averaged across successful replications. Values that were not within the acceptable [-0.05 and 0.05] bound were in bold.

Table 5.7: Relative Bias of the Fixed Effect of Random Slope τ at Between-Time Level

FE	T	PMD	$\omega = 0.60$			$\omega = 0.80$		
			50	N 100	200	50	N 100	200
γ_τ								
0.3	15	0%	-0.098	-0.112	-0.101	-0.089	-0.098	-0.093
		20%	0.638	0.614	0.632	0.264	0.248	0.250
		40%	-0.731	-0.750	-0.731	-0.450	-0.468	-0.444
	30	0%	-0.075	-0.077	-0.037	-0.075	-0.073	-0.036
		20%	0.690	0.684	0.709	0.301	0.302	0.332
		40%	-0.668	-0.670	-0.650	-0.417	-0.418	-0.390
	60	0%	-0.032	-0.022	-0.033	-0.031	-0.023	-0.033
		20%	0.720	0.720	0.716	0.345	0.350	0.342
		40%	-0.597	-0.587	-0.607	-0.360	-0.357	-0.373
	120	0%	-0.002	-0.027	-0.014	-0.008	-0.026	-0.014
		20%	0.721	0.703	0.713	0.363	0.344	0.353
		40%	-0.554	-0.565	-0.559	-0.333	-0.348	-0.343
0.6	15	0%	-1.110	-1.400	-2.230	-0.407	-0.372	-0.424
		20%	-0.258	-0.567	-0.648	-0.517	-0.372	-0.449
		40%	-0.626	-0.611	-0.589	-0.408	-0.419	-0.383
	30	0%	-0.442	-0.080	-0.514	-0.243	-0.075	-0.197
		20%	-1.180	-0.311	-1.670	-0.373	0.027	-0.487
		40%	-0.539	-0.546	-0.523	-0.360	-0.359	-0.336
	60	0%	-0.031	-0.029	-0.016	-0.029	-0.031	-0.016
		20%	0.034	0.000	0.171	0.175	0.175	0.124
		40%	-0.487	-0.480	-0.481	-0.311	-0.307	-0.297
	120	0%	-0.008	-0.009	-0.005	-0.020	-0.009	-0.005
		20%	0.362	-0.370	0.315	0.188	0.118	0.195
		40%	-0.475	-0.449	-0.446	-0.311	-0.284	-0.281

Note: FE = Fixed Effect; N = Sample Size; T = Measurement Occasions; PMD = Planned-Missing Data Percentage; ω = Reliability. The values represent mean parameter relative bias averaged across successful replications. Values that were not within the acceptable [-0.05 and 0.05] bound were in bold.

Table 5.8: Coverage of the Fixed Effect of Random Slope α at Between-Time Level

FE	T	PMD	$\omega = 0.60$			$\omega = 0.80$		
			50	N	200	50	N	200
0.3	15	0%	0.930	0.936	0.913	0.932	0.933	0.913
		20%	0.466	0.382	0.377	0.826	0.795	0.812
		40%	0.335	0.327	0.240	0.786	0.818	0.757
	30	0%	0.916	0.898	0.925	0.910	0.889	0.923
		20%	0.279	0.211	0.198	0.772	0.683	0.703
		40%	0.091	0.097	0.061	0.561	0.591	0.585
	60	0%	0.888	0.916	0.896	0.886	0.912	0.895
		20%	0.108	0.097	0.085	0.585	0.614	0.616
		40%	0.020	0.009	0.012	0.353	0.325	0.296
	120	0%	0.911	0.923	0.893	0.908	0.924	0.894
		20%	0.034	0.015	0.018	0.467	0.389	0.425
		40%	0.002	0.002	0.002	0.146	0.141	0.110
0.6	15	0%	0.928	0.896	0.915	0.925	0.906	0.909
		20%	0.142	0.072	0.082	0.624	0.521	0.531
		40%	0.533	0.637	0.426	0.853	0.877	0.825
	30	0%	0.900	0.901	0.903	0.896	0.897	0.901
		20%	0.063	0.024	0.029	0.457	0.337	0.341
		40%	0.207	0.266	0.144	0.651	0.720	0.632
	60	0%	0.901	0.892	0.913	0.900	0.896	0.911
		20%	0.009	0.007	0.004	0.223	0.195	0.173
		40%	0.076	0.076	0.036	0.498	0.506	0.445
	120	0%	0.911	0.874	0.890	0.914	0.876	0.884
		20%	0.001	0.001	0.000	0.102	0.083	0.091
		40%	0.032	0.012	0.005	0.321	0.301	0.186

Note: FE = Fixed Effect; N = Sample Size; T = Measurement Occasions; PMD = Planned-Missing Data Percentage; ω = Reliability. The values represent the coverage averaged across successful replications. Values that were smaller than the acceptable lower boundary of coverage (i.e. 0.87) were in bold.

Table 5.9: Coverage of the Fixed Effect of Random Slope β at Between-Time Level

FE	T	PMD	$\omega = 0.60$			$\omega = 0.80$		
			50	N 100	200	50	N 100	200
0.3	15	0%	0.932	0.935	0.936	γ_{β_t} 0.929	0.938	0.936
		20%	0.810	0.829	0.851	0.895	0.902	0.917
		40%	0.589	0.538	0.503	0.860	0.867	0.836
	30	0%	0.922	0.923	0.903	0.920	0.922	0.900
		20%	0.747	0.715	0.719	0.855	0.855	0.848
		40%	0.272	0.233	0.206	0.689	0.666	0.641
	60	0%	0.909	0.894	0.902	0.913	0.891	0.905
		20%	0.642	0.630	0.631	0.825	0.801	0.815
		40%	0.090	0.063	0.055	0.483	0.428	0.441
	120	0%	0.900	0.915	0.914	0.895	0.917	0.908
		20%	0.502	0.503	0.520	0.748	0.749	0.784
		40%	0.021	0.010	0.008	0.221	0.239	0.208
0.6	15	0%	0.844	0.850	0.700	0.888	0.891	0.806
		20%	0.630	0.629	0.638	0.786	0.810	0.785
		40%	0.770	0.700	0.459	0.921	0.898	0.770
	30	0%	0.788	0.616	0.631	0.844	0.672	0.702
		20%	0.560	0.475	0.462	0.732	0.673	0.668
		40%	0.426	0.278	0.216	0.735	0.550	0.525
	60	0%	0.869	0.611	0.719	0.886	0.658	0.779
		20%	0.387	0.356	0.345	0.646	0.603	0.641
		40%	0.164	0.091	0.070	0.628	0.369	0.425
	120	0%	0.868	0.775	0.704	0.741	0.808	0.743
		20%	0.216	0.238	0.258	0.477	0.519	0.528
		40%	0.068	0.032	0.038	0.369	0.260	0.239

Note: FE = Fixed Effect; N = Sample Size; T = Measurement Occasions; PMD = Planned-Missing Data Percentage; ω = Reliability. The values represent the coverage averaged across successful replications. Values that were smaller than the acceptable lower boundary of coverage (i.e. 0.87) were in bold.

Table 5.10: Coverage of the Fixed Effect of Random Slope τ at Between-Time Level

FE	T	PMD	$\omega = 0.60$			$\omega = 0.80$		
			50	N	200	50	N	200
0.3	15	0%	0.934	0.939	0.946	0.929	0.940	0.942
		20%	0.627	0.610	0.568	0.894	0.884	0.901
		40%	0.385	0.367	0.346	0.764	0.789	0.787
	30	0%	0.924	0.928	0.912	0.932	0.925	0.910
		20%	0.307	0.281	0.229	0.796	0.766	0.741
		40%	0.236	0.171	0.140	0.677	0.649	0.668
	60	0%	0.898	0.913	0.904	0.900	0.911	0.904
		20%	0.104	0.071	0.063	0.630	0.545	0.524
		40%	0.082	0.066	0.052	0.490	0.455	0.465
	120	0%	0.922	0.907	0.899	0.916	0.905	0.897
		20%	0.011	0.011	0.010	0.329	0.359	0.342
		40%	0.026	0.015	0.022	0.311	0.264	0.295
0.6	15	0%	0.882	0.899	0.898	0.899	0.921	0.917
		20%	0.730	0.690	0.666	0.929	0.921	0.915
		40%	0.105	0.073	0.087	0.486	0.433	0.442
	30	0%	0.926	0.913	0.918	0.923	0.921	0.912
		20%	0.421	0.306	0.221	0.843	0.802	0.731
		40%	0.026	0.013	0.020	0.352	0.242	0.246
	60	0%	0.897	0.898	0.920	0.904	0.894	0.925
		20%	0.110	0.083	0.051	0.582	0.532	0.439
		40%	0.006	0.001	0.002	0.180	0.140	0.151
	120	0%	0.886	0.894	0.902	0.862	0.892	0.907
		20%	0.021	0.013	0.016	0.311	0.289	0.271
		40%	0.000	0.000	0.000	0.106	0.057	0.057

Note: FE = Fixed Effect; N = Sample Size; T = Measurement Occasions; PMD = Planned-Missing Data Percentage; ω = Reliability. The values represent the coverage averaged across successful replications. Values that were smaller than the acceptable lower boundary of coverage (i.e. 0.87) were in bold.

Table 5.11: Rejection of the Fixed Effect of Random Slope α at Between-Time Level

FE	T	PMD	$\omega = 0.60$			$\omega = 0.80$		
			50	N 100	200	50	N 100	200
0.3	15	0%	0.394	0.382	0.445	0.408	0.381	0.450
		20%	0.070	0.072	0.091	0.235	0.235	0.284
		40%	0.980	0.979	0.989	0.806	0.812	0.842
	30	0%	0.680	0.645	0.708	0.678	0.645	0.703
		20%	0.190	0.189	0.176	0.486	0.480	0.495
		40%	1.000	1.000	0.999	0.968	0.973	0.974
	60	0%	0.865	0.873	0.893	0.865	0.869	0.891
		20%	0.306	0.373	0.364	0.676	0.698	0.720
		40%	1.000	1.000	1.000	0.996	0.998	1.000
	120	0%	0.977	0.974	0.981	0.983	0.975	0.981
		20%	0.504	0.506	0.575	0.851	0.819	0.864
		40%	1.000	1.000	1.000	1.000	1.000	1.000
0.6	15	0%	0.799	0.802	0.864	0.817	0.810	0.873
		20%	0.376	0.419	0.467	0.703	0.687	0.753
		40%	1.000	0.978	0.967	0.977	0.964	0.985
	30	0%	0.980	0.968	0.981	0.979	0.968	0.980
		20%	0.651	0.688	0.720	0.904	0.896	0.922
		40%	0.989	0.985	0.990	1.000	1.000	1.000
	60	0%	1.000	1.000	1.000	1.000	1.000	1.000
		20%	0.855	0.892	0.886	0.989	0.986	0.996
		40%	0.988	0.979	0.991	1.000	1.000	1.000
	120	0%	1.000	1.000	1.000	1.000	1.000	1.000
		20%	0.936	0.947	0.956	0.999	1.000	0.998
		40%	1.000	0.996	0.998	1.000	1.000	1.000

Note: FE = Fixed Effect; N = Sample Size; T = Measurement Occasions; PMD = Planned-Missing Data Percentage; ω = Reliability. The values represent the rejection averaged across successful replications. Values that were smaller than the acceptable lower boundary of rejection (i.e., 0.80) were in bold.

Table 5.12: Rejection of the Fixed Effect of Random Slope β at Between-Time Level

FE	T	PMD	$\omega = 0.60$			$\omega = 0.80$		
			50	N	200	50	N	200
γ_{β_i}								
0.3	15	0%	0.341	0.368	0.416	0.359	0.380	0.435
		20%	0.270	0.284	0.327	0.301	0.304	0.362
		40%	0.879	0.907	0.919	0.708	0.742	0.783
	30	0%	0.684	0.688	0.713	0.688	0.691	0.713
		20%	0.606	0.597	0.611	0.616	0.619	0.635
		40%	0.994	0.994	0.995	0.945	0.931	0.936
	60	0%	0.865	0.890	0.881	0.871	0.887	0.886
		20%	0.813	0.845	0.848	0.822	0.842	0.850
		40%	1.000	1.000	1.000	0.995	0.997	0.999
	120	0%	0.984	0.974	0.983	0.989	0.975	0.983
		20%	0.960	0.952	0.967	0.963	0.952	0.969
		40%	1.000	1.000	1.000	1.000	1.000	1.000
0.6	15	0%	0.688	0.804	0.628	0.754	0.837	0.740
		20%	0.822	0.838	0.867	0.802	0.834	0.851
		40%	0.789	0.843	0.479	0.906	0.920	0.756
	30	0%	0.873	0.690	0.713	0.923	0.754	0.785
		20%	0.983	0.976	0.989	0.979	0.937	0.973
		40%	0.564	0.405	0.363	0.820	0.619	0.610
	60	0%	0.968	0.715	0.818	0.986	0.761	0.871
		20%	0.999	1.000	0.999	0.999	0.982	0.996
		40%	0.668	0.400	0.397	0.925	0.582	0.678
	120	0%	1.000	0.855	0.807	1.000	0.886	0.847
		20%	1.000	1.000	1.000	1.000	0.999	0.999
		40%	0.981	0.448	0.450	0.994	0.641	0.587

Note: FE = Fixed Effect; N = Sample Size; T = Measurement Occasions; PMD = Planned-Missing Data Percentage; ω = Reliability. The values represent the rejection averaged across successful replications. Values that were smaller than the acceptable lower boundary of rejection (i.e., 0.80) were in bold.

Table 5.13: Rejection of the Fixed Effect of Random Slope τ at Between-Time Level

FE	T	PMD	$\omega = 0.60$			$\omega = 0.80$		
			50	N 100	200	50	N 100	200
0.3	15	0%	0.328	0.379	0.421	0.332	0.402	0.429
		20%	0.897	0.913	0.930	0.648	0.713	0.740
		40%	0.052	0.051	0.066	0.178	0.202	0.230
	30	0%	0.651	0.647	0.686	0.650	0.651	0.684
		20%	0.988	0.990	0.994	0.903	0.916	0.948
		40%	0.170	0.186	0.244	0.422	0.414	0.487
	60	0%	0.851	0.877	0.883	0.851	0.874	0.884
		20%	1.000	1.000	1.000	0.990	0.989	0.993
		40%	0.401	0.481	0.492	0.676	0.713	0.716
	120	0%	0.987	0.975	0.976	0.987	0.975	0.976
		20%	1.000	1.000	1.000	1.000	1.000	1.000
		40%	0.687	0.667	0.699	0.871	0.847	0.855
0.6	15	0%	0.750	0.799	0.869	0.768	0.816	0.889
		20%	0.987	0.987	0.995	0.952	0.960	0.976
		40%	0.410	0.539	0.644	0.645	0.701	0.805
	30	0%	0.969	0.968	0.981	0.972	0.970	0.982
		20%	0.978	0.993	0.977	0.995	0.998	0.993
		40%	0.834	0.854	0.908	0.917	0.929	0.959
	60	0%	1.000	1.000	1.000	1.000	1.000	1.000
		20%	0.988	0.990	0.996	1.000	1.000	0.999
		40%	0.987	0.997	0.995	0.996	0.998	0.999
	120	0%	1.000	1.000	1.000	1.000	1.000	1.000
		20%	1.000	0.950	0.998	1.000	0.997	1.000
		40%	1.000	1.000	1.000	1.000	1.000	1.000

Note: FE = Fixed Effect; N = Sample Size; T = Measurement Occasions; PMD = Planned-Missing Data Percentage; ω = Reliability. The values represent the rejection averaged across successful replications. Values that were smaller than the acceptable lower boundary of rejection (i.e., 0.80) were in bold.

Table 5.14: Descriptive Statistics for Random Effect of Random Slope α at Between-Time Level

RE	T	PMD	$\omega = 0.60$			$\omega = 0.80$		
			50	N 100	200	50	N 100	200
$\sigma_{\xi_{\alpha t}}^2$								
0.16	15	0%	0.199 (0.123)	0.221 (0.132)	0.192 (0.109)	0.199 (0.123)	0.221 (0.131)	0.189 (0.107)
		20%	0.116 (0.080)	0.121 (0.077)	0.109 (0.065)	0.157 (0.102)	0.168 (0.103)	0.148 (0.085)
		40%	0.080 (0.055)	0.110 (0.069)	0.072 (0.043)	0.134 (0.087)	0.161 (0.099)	0.126 (0.073)
	30	0%	0.179 (0.063)	0.180 (0.061)	0.173 (0.056)	0.179 (0.063)	0.182 (0.061)	0.172 (0.056)
		20%	0.105 (0.041)	0.099 (0.035)	0.095 (0.032)	0.143 (0.052)	0.140 (0.048)	0.134 (0.044)
		40%	0.070 (0.027)	0.077 (0.027)	0.064 (0.021)	0.120 (0.044)	0.126 (0.043)	0.111 (0.037)
	60	0%	0.168 (0.039)	0.171 (0.037)	0.168 (0.035)	0.168 (0.039)	0.172 (0.037)	0.168 (0.035)
		20%	0.092 (0.024)	0.093 (0.021)	0.092 (0.020)	0.130 (0.031)	0.133 (0.029)	0.131 (0.028)
		40%	0.065 (0.017)	0.069 (0.016)	0.064 (0.014)	0.113 (0.027)	0.116 (0.025)	0.110 (0.023)
	120	0%	0.164 (0.025)	0.165 (0.024)	0.164 (0.023)	0.165 (0.025)	0.165 (0.024)	0.164 (0.023)
		20%	0.089 (0.015)	0.091 (0.014)	0.092 (0.013)	0.126 (0.020)	0.128 (0.019)	0.128 (0.018)
		40%	0.071 (0.012)	0.065 (0.010)	0.064 (0.009)	0.114 (0.018)	0.109 (0.016)	0.107 (0.015)
0.64	15	0%	0.781 (0.439)	0.810 (0.462)	0.773 (0.422)	0.780 (0.438)	0.813 (0.464)	0.773 (0.422)
		20%	0.359 (0.215)	0.362 (0.212)	0.351 (0.196)	0.545 (0.314)	0.554 (0.319)	0.531 (0.293)
		40%	0.227 (0.137)	0.282 (0.165)	0.225 (0.125)	0.432 (0.250)	0.482 (0.279)	0.430 (0.238)
	30	0%	0.701 (0.229)	0.723 (0.232)	0.701 (0.223)	0.702 (0.229)	0.724 (0.233)	0.700 (0.223)
		20%	0.304 (0.105)	0.314 (0.103)	0.302 (0.097)	0.482 (0.160)	0.493 (0.160)	0.476 (0.152)
		40%	0.201 (0.069)	0.215 (0.071)	0.194 (0.063)	0.381 (0.127)	0.414 (0.135)	0.384 (0.123)
	60	0%	0.662 (0.139)	0.680 (0.140)	0.674 (0.137)	0.661 (0.139)	0.681 (0.140)	0.675 (0.137)
		20%	0.284 (0.063)	0.293 (0.062)	0.289 (0.060)	0.451 (0.097)	0.465 (0.097)	0.458 (0.094)
		40%	0.187 (0.042)	0.198 (0.042)	0.186 (0.038)	0.358 (0.077)	0.377 (0.079)	0.374 (0.077)
	120	0%	0.654 (0.091)	0.667 (0.093)	0.654 (0.088)	0.653 (0.090)	0.667 (0.093)	0.654 (0.088)
		20%	0.281 (0.041)	0.280 (0.040)	0.277 (0.038)	0.447 (0.063)	0.453 (0.064)	0.444 (0.060)
		40%	0.193 (0.028)	0.199 (0.028)	0.190 (0.026)	0.354 (0.050)	0.365 (0.051)	0.356 (0.048)

Note: RE = Random Effect; N = Sample Size; T = Measurement Occasions; PMD = Planned-Missing Data Percentage; ω = Reliability. The values outside the brackets represent the average point-estimate of the parameter across the successful replications. The values enclosed in the brackets represent the average standard deviation of the posterior distribution of the parameter across the successful replications.

Table 5.15: Descriptive Statistics for Random Effect of Random Slope β at Between-Time Level

RE	T	PMD	$\omega = 0.60$			$\omega = 0.80$			
			50	N 100	200	50	N 100	200	
						$\sigma_{\xi\beta}^2$			
0.16	15	0%	0.209 (0.147)	0.208 (0.127)	0.203 (0.117)	0.208 (0.146)	0.205 (0.125)	0.204 (0.117)	
		20%	0.136 (0.100)	0.136 (0.086)	0.135 (0.079)	0.171 (0.123)	0.171 (0.105)	0.170 (0.098)	
		40%	0.117 (0.090)	0.105 (0.067)	0.101 (0.062)	0.157 (0.115)	0.148 (0.092)	0.147 (0.087)	
	30	0%	0.178 (0.062)	0.178 (0.059)	0.178 (0.058)	0.178 (0.062)	0.178 (0.059)	0.178 (0.059)	
		20%	0.117 (0.043)	0.115 (0.039)	0.115 (0.038)	0.148 (0.053)	0.147 (0.049)	0.148 (0.049)	
		40%	0.090 (0.034)	0.090 (0.031)	0.088 (0.030)	0.131 (0.047)	0.130 (0.044)	0.127 (0.042)	
	60	0%	0.170 (0.038)	0.169 (0.036)	0.171 (0.036)	0.170 (0.038)	0.169 (0.035)	0.170 (0.036)	
		20%	0.109 (0.026)	0.109 (0.023)	0.110 (0.023)	0.140 (0.032)	0.140 (0.030)	0.141 (0.030)	
		40%	0.086 (0.021)	0.086 (0.019)	0.085 (0.018)	0.125 (0.029)	0.123 (0.026)	0.123 (0.026)	
	120	0%	0.165 (0.024)	0.165 (0.024)	0.165 (0.023)	0.165 (0.024)	0.165 (0.024)	0.165 (0.023)	
		20%	0.105 (0.016)	0.107 (0.016)	0.107 (0.015)	0.136 (0.020)	0.136 (0.020)	0.137 (0.019)	
		40%	0.086 (0.014)	0.083 (0.012)	0.084 (0.012)	0.122 (0.019)	0.120 (0.018)	0.119 (0.017)	
0.64	15	0%	0.806 (0.519)	0.794 (0.461)	0.797 (0.439)	0.798 (0.514)	0.793 (0.460)	0.792 (0.437)	
		20%	0.486 (0.320)	0.489 (0.287)	0.480 (0.267)	0.625 (0.407)	0.627 (0.366)	0.616 (0.341)	
		40%	0.412 (0.277)	0.383 (0.226)	0.384 (0.216)	0.565 (0.372)	0.542 (0.318)	0.540 (0.301)	
	30	0%	0.719 (0.231)	0.708 (0.223)	0.709 (0.227)	0.720 (0.231)	0.706 (0.223)	0.710 (0.227)	
		20%	0.423 (0.139)	0.421 (0.135)	0.427 (0.138)	0.558 (0.181)	0.554 (0.176)	0.557 (0.179)	
		40%	0.352 (0.118)	0.328 (0.106)	0.329 (0.107)	0.494 (0.162)	0.480 (0.153)	0.482 (0.155)	
	60	0%	0.674 (0.140)	0.671 (0.136)	0.678 (0.139)	0.673 (0.140)	0.671 (0.136)	0.678 (0.139)	
		20%	0.397 (0.084)	0.399 (0.082)	0.399 (0.082)	0.526 (0.110)	0.528 (0.107)	0.529 (0.109)	
		40%	0.317 (0.068)	0.317 (0.065)	0.310 (0.064)	0.460 (0.097)	0.460 (0.094)	0.465 (0.096)	
	120	0%	0.659 (0.090)	0.655 (0.091)	0.658 (0.090)	0.656 (0.090)	0.654 (0.091)	0.658 (0.090)	
		20%	0.389 (0.054)	0.384 (0.054)	0.386 (0.053)	0.516 (0.071)	0.512 (0.071)	0.513 (0.070)	
		40%	0.317 (0.045)	0.311 (0.044)	0.315 (0.044)	0.450 (0.063)	0.447 (0.063)	0.451 (0.062)	

Note: RE = Random Effect; N = Sample Size; T = Measurement Occasions; PMD = Planned-Missing Data Percentage; ω = Reliability. The values outside the brackets represent the average point-estimate of the parameter across the successful replications. The values enclosed in the brackets represent the average standard deviation of the posterior distribution of the parameter across the successful replications.

Table 5.16: Descriptive Statistics for Random Effect of Random Slope τ at Between-Time Level

RE	T	PMD	$\omega = 0.60$			$\sigma_{\xi_{\tau}}^2$	$\omega = 0.80$		
			50	N 100	200		50	N 100	200
0.16	15	0%	0.205 (0.142)	0.213 (0.140)	0.199 (0.114)		0.205 (0.142)	0.212 (0.139)	0.198 (0.113)
		20%	0.122 (0.090)	0.127 (0.088)	0.118 (0.070)		0.161 (0.115)	0.167 (0.112)	0.156 (0.090)
		40%	0.093 (0.070)	0.095 (0.067)	0.089 (0.053)		0.143 (0.103)	0.143 (0.097)	0.135 (0.079)
	30	0%	0.183 (0.066)	0.183 (0.060)	0.178 (0.058)		0.182 (0.066)	0.183 (0.060)	0.178 (0.057)
		20%	0.109 (0.042)	0.106 (0.036)	0.102 (0.034)		0.145 (0.054)	0.143 (0.048)	0.139 (0.045)
		40%	0.079 (0.032)	0.080 (0.028)	0.077 (0.026)		0.125 (0.047)	0.123 (0.042)	0.118 (0.039)
	60	0%	0.170 (0.037)	0.168 (0.036)	0.167 (0.034)		0.169 (0.037)	0.170 (0.036)	0.168 (0.034)
		20%	0.096 (0.023)	0.096 (0.021)	0.096 (0.020)		0.132 (0.030)	0.132 (0.029)	0.131 (0.027)
		40%	0.073 (0.018)	0.073 (0.016)	0.072 (0.015)		0.116 (0.027)	0.113 (0.025)	0.112 (0.023)
	120	0%	0.164 (0.024)	0.164 (0.024)	0.163 (0.023)		0.164 (0.024)	0.164 (0.024)	0.163 (0.023)
		20%	0.092 (0.014)	0.095 (0.014)	0.094 (0.013)		0.128 (0.019)	0.128 (0.019)	0.128 (0.018)
		40%	0.076 (0.012)	0.070 (0.011)	0.071 (0.010)		0.116 (0.018)	0.110 (0.016)	0.109 (0.015)
0.64	15	0%	0.774 (0.494)	0.820 (0.511)	0.768 (0.425)	0.775 (0.495)	0.819 (0.511)	0.761 (0.422)	
		20%	0.386 (0.260)	0.419 (0.269)	0.383 (0.220)	0.548 (0.358)	0.592 (0.375)	0.546 (0.308)	
		40%	0.281 (0.191)	0.297 (0.192)	0.291 (0.164)	0.443 (0.292)	0.478 (0.303)	0.452 (0.254)	
	30	0%	0.723 (0.239)	0.714 (0.221)	0.702 (0.220)	0.724 (0.240)	0.713 (0.221)	0.702 (0.220)	
		20%	0.339 (0.118)	0.342 (0.109)	0.332 (0.106)	0.505 (0.172)	0.503 (0.158)	0.488 (0.154)	
		40%	0.251 (0.089)	0.242 (0.078)	0.238 (0.076)	0.416 (0.142)	0.409 (0.129)	0.400 (0.127)	
	60	0%	0.671 (0.134)	0.667 (0.135)	0.675 (0.135)	0.671 (0.134)	0.667 (0.135)	0.676 (0.135)	
		20%	0.307 (0.064)	0.312 (0.065)	0.313 (0.064)	0.463 (0.095)	0.466 (0.096)	0.467 (0.094)	
		40%	0.226 (0.048)	0.226 (0.047)	0.223 (0.045)	0.379 (0.078)	0.381 (0.079)	0.387 (0.078)	
	120	0%	0.657 (0.088)	0.656 (0.090)	0.656 (0.088)	0.659 (0.088)	0.656 (0.090)	0.656 (0.088)	
		20%	0.304 (0.042)	0.299 (0.042)	0.299 (0.041)	0.456 (0.062)	0.452 (0.063)	0.451 (0.061)	
		40%	0.227 (0.032)	0.223 (0.032)	0.223 (0.031)	0.372 (0.051)	0.370 (0.052)	0.371 (0.050)	

Note: RE = Random Effect; N = Sample Size; T = Measurement Occasions; PMD = Planned-Missing Data Percentage; ω = Reliability. The values outside the brackets represent the average point-estimate of the parameter across the successful replications. The values enclosed in the brackets represent the average standard deviation of the posterior distribution of the parameter across the successful replications.

Table 5.17: Relative Bias of the Random Effect of Random Slope α at Between-Time Level

RE	T	PMD	$\omega = 0.60$			$\sigma_{\epsilon_{it}}^2$	$\omega = 0.80$		
			50	N 100	200		50	N 100	200
0.16	15	0%	0.242	0.382	0.203		0.244	0.380	0.180
		20%	-0.277	-0.242	-0.318		-0.018	0.053	-0.078
		40%	-0.499	-0.316	-0.547		-0.163	0.006	-0.214
	30	0%	0.119	0.125	0.079		0.117	0.139	0.076
		20%	-0.347	-0.378	-0.405		-0.109	-0.128	-0.162
		40%	-0.560	-0.521	-0.601		-0.252	-0.215	-0.306
	60	0%	0.052	0.070	0.050		0.050	0.077	0.052
		20%	-0.424	-0.416	-0.422		-0.186	-0.166	-0.182
		40%	-0.591	-0.570	-0.601		-0.296	-0.277	-0.312
	120	0%	0.025	0.031	0.027		0.029	0.033	0.026
		20%	-0.445	-0.429	-0.426		-0.211	-0.199	-0.200
		40%	-0.559	-0.594	-0.600		-0.290	-0.317	-0.331
0.64	15	0%	0.221	0.266	0.208	0.218	0.271	0.208	
		20%	-0.438	-0.434	-0.451	-0.148	-0.135	-0.170	
		40%	-0.645	-0.559	-0.648	-0.325	-0.247	-0.328	
	30	0%	0.096	0.130	0.096	0.097	0.131	0.093	
		20%	-0.526	-0.510	-0.528	-0.248	-0.229	-0.256	
		40%	-0.686	-0.664	-0.697	-0.404	-0.353	-0.400	
	60	0%	0.034	0.062	0.054	0.033	0.064	0.054	
		20%	-0.556	-0.543	-0.549	-0.296	-0.273	-0.284	
		40%	-0.707	-0.690	-0.709	-0.441	-0.411	-0.415	
	120	0%	0.023	0.042	0.022	0.021	0.042	0.022	
		20%	-0.561	-0.562	-0.567	-0.301	-0.293	-0.306	
		40%	-0.699	-0.690	-0.703	-0.446	-0.430	-0.444	

Note: RE = Random Effect; N = Sample Size; T = Measurement Occasions; PMD = Planned-Missing Data Percentage; ω = Reliability. The values represent mean parameter relative bias averaged across successful replications. Values that were not within the acceptable [-0.05 and 0.05] bound were in bold.

Table 5.18: Relative Bias of the Random Effect of Random Slope β at Between-Time Level

RE	T	PMD	$\omega = 0.60$			$\omega = 0.80$		
			N			N		
			50	100	200	50	100	200
$\sigma_{\xi_{\beta_r}}^2$								
0.16	15	0%	0.306	0.301	0.268	0.302	0.280	0.273
		20%	-0.152	-0.147	-0.156	0.071	0.067	0.063
		40%	-0.267	-0.345	-0.367	-0.021	-0.077	-0.079
	30	0%	0.111	0.112	0.112	0.112	0.111	0.116
		20%	-0.267	-0.280	-0.282	-0.072	-0.079	-0.077
		40%	-0.440	-0.437	-0.450	-0.181	-0.188	-0.207
	60	0%	0.064	0.056	0.066	0.065	0.055	0.064
		20%	-0.316	-0.320	-0.315	-0.126	-0.126	-0.122
		40%	-0.465	-0.465	-0.470	-0.217	-0.233	-0.230
	120	0%	0.031	0.030	0.032	0.032	0.029	0.033
		20%	-0.342	-0.332	-0.330	-0.152	-0.148	-0.145
		40%	-0.465	-0.482	-0.476	-0.238	-0.251	-0.254
0.64	15	0%	0.260	0.241	0.245	0.247	0.240	0.238
		20%	-0.241	-0.235	-0.250	-0.023	-0.020	-0.038
		40%	-0.357	-0.402	-0.401	-0.116	-0.153	-0.157
	30	0%	0.124	0.106	0.107	0.124	0.102	0.109
		20%	-0.339	-0.342	-0.332	-0.129	-0.135	-0.130
		40%	-0.450	-0.487	-0.485	-0.228	-0.250	-0.247
	60	0%	0.053	0.049	0.059	0.051	0.049	0.059
		20%	-0.380	-0.377	-0.377	-0.178	-0.175	-0.174
		40%	-0.505	-0.505	-0.515	-0.281	-0.281	-0.273
	120	0%	0.029	0.023	0.028	0.025	0.023	0.028
		20%	-0.392	-0.400	-0.397	-0.194	-0.200	-0.198
		40%	-0.505	-0.514	-0.507	-0.297	-0.301	-0.295

Note: RE = Random Effect; N = Sample Size; T = Measurement Occasions; PMD = Planned-Missing Data Percentage; ω = Reliability. The values represent mean parameter relative bias averaged across successful replications. Values that were not within the acceptable [-0.05 and 0.05] bound were in bold.

Table 5.19: Relative Bias of the Random Effect of Random Slope τ at Between-Time Level

RE	T	PMD	$\omega = 0.60$			$\sigma_{\xi_{\tau}}^2$	$\omega = 0.80$		
			50	N 100	200		50	N 100	200
0.16	15	0%	0.282	0.331	0.242		0.282	0.323	0.235
		20%	-0.239	-0.209	-0.265		0.008	0.042	-0.028
		40%	-0.417	-0.406	-0.441		-0.108	-0.103	-0.159
	30	0%	0.142	0.143	0.116		0.140	0.143	0.115
		20%	-0.321	-0.339	-0.362		-0.094	-0.105	-0.129
		40%	-0.504	-0.503	-0.519		-0.219	-0.229	-0.260
	60	0%	0.061	0.053	0.046		0.057	0.060	0.048
		20%	-0.401	-0.401	-0.400		-0.173	-0.173	-0.180
		40%	-0.542	-0.545	-0.552		-0.274	-0.291	-0.298
	120	0%	0.027	0.026	0.019		0.028	0.026	0.019
		20%	-0.422	-0.409	-0.410		-0.203	-0.197	-0.203
		40%	-0.524	-0.564	-0.557		-0.274	-0.313	-0.321
0.64	15	0%	0.209	0.282	0.199	0.211	0.280	0.189	
		20%	-0.396	-0.346	-0.402	-0.144	-0.075	-0.147	
		40%	-0.560	-0.536	-0.546	-0.308	-0.253	-0.293	
	30	0%	0.129	0.115	0.096	0.131	0.114	0.097	
		20%	-0.470	-0.466	-0.481	-0.211	-0.214	-0.238	
		40%	-0.608	-0.623	-0.629	-0.350	-0.361	-0.376	
	60	0%	0.048	0.042	0.055	0.048	0.042	0.057	
		20%	-0.520	-0.512	-0.511	-0.276	-0.271	-0.270	
		40%	-0.647	-0.647	-0.652	-0.408	-0.405	-0.395	
	120	0%	0.027	0.024	0.025	0.030	0.024	0.025	
		20%	-0.525	-0.533	-0.532	-0.288	-0.293	-0.295	
		40%	-0.645	-0.651	-0.651	-0.419	-0.422	-0.420	

Note: RE = Random Effect; N = Sample Size; T = Measurement Occasions; PMD = Planned-Missing Data Percentage; ω = Reliability. The values represent mean parameter relative bias averaged across successful replications. Values that were not within the acceptable [-0.05 and 0.05] bound were in bold.

Table 5.20: Coverage of the Random Effect of Random Slope α at Between-Time Level

RE	T	PMD	$\omega = 0.60$			$\omega = 0.80$		
			50	N	200	50	N	200
0.16	15	0%	0.922	0.891	0.938	0.926	0.891	0.936
		20%	0.716	0.734	0.663	0.878	0.888	0.855
		40%	0.456	0.471	0.310	0.798	0.804	0.752
	30	0%	0.919	0.899	0.916	0.909	0.884	0.915
		20%	0.539	0.429	0.358	0.851	0.804	0.770
		40%	0.151	0.172	0.064	0.678	0.614	0.535
	60	0%	0.916	0.880	0.916	0.919	0.880	0.916
		20%	0.206	0.177	0.141	0.700	0.680	0.646
		40%	0.022	0.043	0.007	0.431	0.453	0.320
	120	0%	0.907	0.890	0.913	0.910	0.891	0.916
		20%	0.044	0.045	0.019	0.478	0.492	0.469
		40%	0.004	0.002	0.000	0.252	0.194	0.120
0.64	15	0%	0.914	0.938	0.932	0.918	0.933	0.931
		20%	0.484	0.479	0.442	0.808	0.830	0.797
		40%	0.181	0.295	0.170	0.610	0.702	0.646
	30	0%	0.922	0.919	0.902	0.922	0.923	0.899
		20%	0.162	0.176	0.160	0.665	0.639	0.643
		40%	0.025	0.035	0.017	0.378	0.426	0.378
	60	0%	0.919	0.913	0.910	0.917	0.916	0.910
		20%	0.046	0.030	0.024	0.419	0.432	0.404
		40%	0.000	0.001	0.000	0.153	0.170	0.140
	120	0%	0.903	0.902	0.899	0.889	0.902	0.902
		20%	0.004	0.003	0.002	0.215	0.219	0.200
		40%	0.000	0.000	0.000	0.030	0.040	0.025

Note: RE = Random Effect; N = Sample Size; T = Measurement Occasions; PMD = Planned-Missing Data Percentage; ω = Reliability. The values represent the coverage averaged across successful replications. Values that were smaller than the acceptable lower boundary of coverage (i.e., 0.87) were in bold.

Table 5.21: Coverage of the Random Effect of Random Slope β at Between-Time Level

RE	T	PMD	$\omega = 0.60$			$\omega = 0.80$		
			50	N 100	200	50	N 100	200
0.16	15	0%	0.949	0.935	0.936	0.953	0.930	0.938
		20%	0.876	0.828	0.837	0.957	0.911	0.914
		40%	0.745	0.644	0.638	0.923	0.871	0.881
	30	0%	0.919	0.914	0.915	0.915	0.917	0.922
		20%	0.653	0.605	0.592	0.890	0.863	0.874
		40%	0.338	0.294	0.265	0.763	0.746	0.748
	60	0%	0.914	0.933	0.912	0.924	0.926	0.911
		20%	0.388	0.317	0.321	0.788	0.788	0.770
		40%	0.110	0.061	0.062	0.605	0.564	0.548
	120	0%	0.895	0.909	0.921	0.899	0.915	0.923
		20%	0.115	0.110	0.113	0.618	0.642	0.649
		40%	0.018	0.003	0.000	0.380	0.304	0.278
0.64	15	0%	0.953	0.927	0.946	0.954	0.928	0.944
		20%	0.777	0.764	0.749	0.921	0.898	0.901
		40%	0.648	0.530	0.549	0.865	0.814	0.828
	30	0%	0.915	0.923	0.924	0.914	0.924	0.928
		20%	0.478	0.433	0.495	0.805	0.798	0.814
		40%	0.289	0.183	0.222	0.664	0.619	0.655
	60	0%	0.919	0.908	0.917	0.919	0.907	0.918
		20%	0.211	0.188	0.210	0.649	0.645	0.657
		40%	0.057	0.040	0.049	0.432	0.393	0.429
	120	0%	0.895	0.897	0.911	0.894	0.899	0.909
		20%	0.069	0.053	0.045	0.472	0.441	0.481
		40%	0.009	0.004	0.003	0.198	0.185	0.202

Note: RE = Random Effect; N = Sample Size; T = Measurement Occasions; PMD = Planned-Missing Data Percentage; ω = Reliability. The values represent the coverage averaged across successful replications. Values that were smaller than the acceptable lower boundary of coverage (i.e., 0.87) were in bold.

Table 5.22: Coverage of the Random Effect of Random Slope τ at Between-Time Level

RE	T	PMD	$\omega = 0.60$			$\omega = 0.80$		
			50	N 100	200	50	N 100	200
0.16	15	0%	0.965	0.933	0.942	0.959	0.935	0.941
		20%	0.784	0.789	0.743	0.915	0.912	0.909
		40%	0.600	0.589	0.482	0.869	0.866	0.838
	30	0%	0.914	0.901	0.918	0.914	0.901	0.915
		20%	0.567	0.469	0.422	0.852	0.819	0.814
		40%	0.235	0.172	0.146	0.721	0.667	0.630
	60	0%	0.900	0.927	0.910	0.902	0.921	0.909
		20%	0.207	0.190	0.175	0.707	0.659	0.668
		40%	0.039	0.028	0.014	0.487	0.396	0.372
	120	0%	0.897	0.892	0.929	0.894	0.893	0.927
		20%	0.050	0.035	0.013	0.484	0.474	0.467
		40%	0.000	0.000	0.000	0.268	0.170	0.119
0.64	15	0%	0.948	0.935	0.934	0.952	0.933	0.937
		20%	0.571	0.627	0.548	0.842	0.868	0.821
		40%	0.319	0.349	0.286	0.689	0.745	0.670
	30	0%	0.923	0.916	0.913	0.924	0.915	0.909
		20%	0.242	0.230	0.196	0.706	0.696	0.673
		40%	0.068	0.033	0.025	0.460	0.405	0.384
	60	0%	0.917	0.904	0.921	0.912	0.906	0.919
		20%	0.048	0.050	0.045	0.432	0.442	0.446
		40%	0.002	0.000	0.002	0.151	0.155	0.169
	120	0%	0.888	0.909	0.908	0.887	0.910	0.907
		20%	0.005	0.004	0.002	0.228	0.207	0.196
		40%	0.000	0.000	0.000	0.046	0.034	0.039

Note: RE = Random Effect; N = Sample Size; T = Measurement Occasions; PMD = Planned-Missing Data Percentage; ω = Reliability. The values represent the coverage averaged across successful replications. Values that were smaller than the acceptable lower boundary of coverage (i.e., 0.87) were in bold.

Table 5.23: Rejection of the Random Effect of Random Slope α at Between-Time Level

RE	T	PMD	$\omega = 0.60$			$\sigma_{\epsilon_{\alpha t}}^2$	$\omega = 0.80$		
			50	N 100	200		50	N 100	200
0.16	15	0%	0.701	0.786	0.803		0.704	0.780	0.780
		20%	0.247	0.327	0.298		0.472	0.578	0.561
		40%	0.093	0.209	0.090		0.366	0.477	0.416
	30	0%	0.953	0.958	0.984		0.953	0.959	0.984
		20%	0.480	0.496	0.535		0.827	0.859	0.896
		40%	0.164	0.220	0.164		0.669	0.719	0.718
	60	0%	0.999	0.999	1.000		0.999	0.999	1.000
		20%	0.632	0.736	0.774		0.963	0.983	0.988
		40%	0.246	0.359	0.304		0.898	0.924	0.944
	120	0%	1.000	1.000	1.000		1.000	1.000	1.000
		20%	0.790	0.886	0.932		0.995	1.000	1.000
		40%	0.538	0.449	0.468		0.996	0.989	0.990
0.64	15	0%	0.999	1.000	1.000	0.999	1.000	1.000	
		20%	0.893	0.928	0.940	0.984	0.996	0.997	
		40%	0.726	0.815	0.764	0.960	0.993	0.981	
	30	0%	1.000	1.000	1.000	1.000	1.000	1.000	
		20%	0.973	0.987	0.994	1.000	1.000	1.000	
		40%	0.908	0.872	0.880	0.999	0.997	0.997	
	60	0%	1.000	1.000	1.000	1.000	1.000	1.000	
		20%	0.989	0.997	0.996	1.000	1.000	1.000	
		40%	0.930	0.950	0.916	0.997	1.000	0.999	
	120	0%	1.000	1.000	1.000	1.000	1.000	1.000	
		20%	0.996	0.999	0.993	1.000	1.000	1.000	
		40%	0.986	0.980	0.977	1.000	1.000	1.000	

Note: RE = Random Effect; N = Sample Size; T = Measurement Occasions; PMD = Planned-Missing Data Percentage; ω = Reliability. The values represent the rejection averaged across successful replications. Values that were smaller than the acceptable lower boundary of rejection (i.e., 0.80) were in bold.

Table 5.24: Rejection of the Random Effect of Random Slope β at Between-Time Level

RE	T	PMD	$\omega = 0.60$			σ_{ξ}^2 ξ_{β_i}	$\omega = 0.80$		
			50	N 100	200		50	N 100	200
0.16	15	0%	0.718	0.791	0.827	0.713	0.777	0.822	
		20%	0.332	0.453	0.493	0.549	0.651	0.694	
		40%	0.189	0.224	0.216	0.446	0.517	0.570	
	30	0%	0.959	0.975	0.990	0.959	0.974	0.990	
		20%	0.683	0.729	0.794	0.900	0.917	0.945	
		40%	0.362	0.432	0.443	0.771	0.843	0.866	
	60	0%	1.000	1.000	1.000	1.000	1.000	1.000	
		20%	0.898	0.946	0.966	0.990	0.996	0.999	
		40%	0.594	0.689	0.690	0.964	0.982	0.992	
	120	0%	1.000	1.000	1.000	1.000	1.000	1.000	
		20%	0.987	0.993	0.999	1.000	1.000	1.000	
		40%	0.856	0.872	0.919	1.000	1.000	1.000	
0.64	15	0%	0.999	1.000	1.000	0.999	1.000	1.000	
		20%	0.992	0.996	0.995	0.997	0.999	0.997	
		40%	0.946	0.973	0.977	0.998	0.998	0.995	
	30	0%	1.000	1.000	1.000	1.000	1.000	1.000	
		20%	0.999	1.000	1.000	1.000	1.000	1.000	
		40%	0.999	1.000	1.000	1.000	1.000	1.000	
	60	0%	1.000	1.000	1.000	1.000	1.000	1.000	
		20%	1.000	1.000	1.000	1.000	1.000	1.000	
		40%	1.000	1.000	1.000	1.000	1.000	1.000	
	120	0%	1.000	1.000	1.000	1.000	1.000	1.000	
		20%	1.000	1.000	1.000	1.000	1.000	1.000	
		40%	1.000	1.000	0.999	1.000	1.000	1.000	

Note: RE = Random Effect; N = Sample Size; T = Measurement Occasions; PMD = Planned-Missing Data Percentage; ω = Reliability. The values represent the rejection averaged across successful replications. Values that were smaller than the acceptable lower boundary of rejection (i.e., 0.80) were in bold.

Table 5.25: Rejection of the Random Effect of Random Slope τ at Between-Time Level

RE	T	PMD	$\omega = 0.60$			$\omega = 0.80$		
			50	N 100	200	50	N 100	200
0.16	15	0%	0.644	0.788	0.821	0.651	0.785	0.805
		20%	0.226	0.332	0.332	0.454	0.595	0.629
		40%	0.096	0.151	0.165	0.363	0.462	0.474
	30	0%	0.943	0.976	0.988	0.941	0.974	0.989
		20%	0.536	0.593	0.611	0.820	0.896	0.905
		40%	0.226	0.274	0.290	0.696	0.749	0.800
	60	0%	0.999	1.000	1.000	0.999	1.000	1.000
		20%	0.730	0.803	0.845	0.963	0.989	0.995
		40%	0.376	0.403	0.445	0.895	0.944	0.956
	120	0%	1.000	1.000	1.000	1.000	1.000	1.000
		20%	0.898	0.955	0.961	0.999	1.000	1.000
		40%	0.664	0.570	0.648	0.998	0.987	0.999
0.64	15	0%	0.999	0.999	1.000	1.000	0.999	1.000
		20%	0.912	0.977	0.978	0.987	0.999	0.996
		40%	0.786	0.903	0.917	0.959	0.993	0.995
	30	0%	1.000	1.000	1.000	1.000	1.000	1.000
		20%	0.996	1.000	0.999	1.000	1.000	1.000
		40%	0.967	0.964	0.977	1.000	1.000	1.000
	60	0%	1.000	1.000	1.000	1.000	1.000	1.000
		20%	0.999	0.999	1.000	1.000	1.000	1.000
		40%	0.989	0.988	0.984	1.000	1.000	1.000
	120	0%	1.000	1.000	1.000	1.000	1.000	1.000
		20%	0.998	0.999	0.998	1.000	1.000	1.000
		40%	0.999	0.996	0.996	1.000	1.000	1.000

Note: RE = Random Effect; N = Sample Size; T = Measurement Occasions; PMD = Planned-Missing Data Percentage; ω = Reliability. The values represent the rejection averaged across successful replications. Values that were smaller than the acceptable lower boundary of rejection (i.e., 0.80) were in bold.

5.4.3 Random Intercept at Between-Time Level

Random Effect ($\sigma_{\xi_{X_t}}^2, \sigma_{\xi_{M_t}}^2, \sigma_{\xi_{Y_t}}^2$)

The random effect (variance) of the random intercepts at the between-time level was simulated with a population value of 0 (i.e., absence of time-varying intercepts). An inspect of the average point-estimate of the parameters and the corresponding average standard deviation of the posterior distributions over successful replications (see Table 5.26, Table 5.27, and Table 5.28) showed that both the point-estimates and the standard deviation of the posterior distributions were small and close to 0. This suggested that the estimator was able to correctly estimate the parameter with high certainty.

Rejection As evident in Table 5.29, Table 5.30, and Table 5.31, the rejection for the parameters were all 0.00 for all combinations of the simulation conditions. This indicated that all the 90% HDIs contained the ROPE, implying that the hypotheses that the parameter was 0 were correctly accepted for all conditions.

Table 5.26: Descriptive Statistics for Random Effect of Random Intercept of X at Between-Time Level

FE	RE	T	PMD	$\omega = 0.60$			$\omega = 0.80$			
				50	N 100	200	50	N 100	200	
0.3	0.16	15	0%	0.009 (0.012)	0.004 (0.006)	0.003 (0.004)	$\sigma_{\xi_{X_i}}^2$	0.009 (0.012)	0.004 (0.006)	0.003 (0.004)
			20%	0.012 (0.016)	0.006 (0.008)	0.003 (0.005)		0.010 (0.014)	0.005 (0.007)	0.003 (0.004)
			40%	0.012 (0.017)	0.006 (0.009)	0.004 (0.005)		0.011 (0.015)	0.005 (0.007)	0.003 (0.004)
		30	0%	0.005 (0.005)	0.003 (0.002)	0.002 (0.002)		0.005 (0.005)	0.003 (0.002)	0.002 (0.002)
			20%	0.007 (0.007)	0.003 (0.003)	0.002 (0.002)		0.006 (0.005)	0.003 (0.003)	0.002 (0.002)
			40%	0.007 (0.007)	0.003 (0.003)	0.002 (0.002)		0.006 (0.006)	0.003 (0.003)	0.002 (0.002)
		60	0%	0.002 (0.002)	0.002 (0.001)	0.001 (0.001)		0.002 (0.002)	0.002 (0.001)	0.001 (0.001)
			20%	0.003 (0.003)	0.002 (0.002)	0.001 (0.001)		0.003 (0.003)	0.002 (0.002)	0.001 (0.001)
			40%	0.003 (0.003)	0.002 (0.002)	0.002 (0.001)		0.003 (0.003)	0.002 (0.002)	0.001 (0.001)
		120	0%	0.002 (0.001)	0.001 (0.001)	0.001 (0.001)		0.002 (0.001)	0.001 (0.001)	0.001 (0.001)
			20%	0.003 (0.002)	0.002 (0.001)	0.001 (0.001)		0.002 (0.002)	0.002 (0.001)	0.001 (0.001)
			40%	0.003 (0.002)	0.002 (0.001)	0.001 (0.001)		0.002 (0.002)	0.002 (0.001)	0.001 (0.001)
	0.64	15	0%	0.006 (0.009)	0.003 (0.005)	0.002 (0.003)	0.006 (0.009)	0.003 (0.005)	0.002 (0.003)	
			20%	0.011 (0.015)	0.006 (0.009)	0.003 (0.005)	0.009 (0.012)	0.005 (0.007)	0.003 (0.004)	
			40%	0.012 (0.018)	0.006 (0.009)	0.004 (0.005)	0.010 (0.014)	0.005 (0.007)	0.003 (0.004)	
		30	0%	0.004 (0.004)	0.002 (0.002)	0.001 (0.001)	0.004 (0.004)	0.002 (0.002)	0.001 (0.001)	
			20%	0.007 (0.007)	0.003 (0.003)	0.002 (0.002)	0.006 (0.005)	0.003 (0.002)	0.001 (0.001)	
			40%	0.008 (0.007)	0.004 (0.004)	0.002 (0.002)	0.006 (0.006)	0.003 (0.003)	0.002 (0.002)	
		60	0%	0.002 (0.002)	0.001 (0.001)	0.001 (0.001)	0.002 (0.002)	0.001 (0.001)	0.001 (0.001)	
			20%	0.004 (0.003)	0.002 (0.002)	0.002 (0.001)	0.003 (0.002)	0.002 (0.001)	0.001 (0.001)	
			40%	0.004 (0.003)	0.003 (0.002)	0.002 (0.001)	0.003 (0.002)	0.002 (0.002)	0.001 (0.001)	
		120	0%	0.001 (0.001)	0.001 (0.001)	0.001 (0.000)	0.001 (0.001)	0.001 (0.001)	0.001 (0.000)	
			20%	0.003 (0.002)	0.002 (0.001)	0.001 (0.001)	0.002 (0.001)	0.002 (0.001)	0.001 (0.001)	
			40%	0.004 (0.002)	0.002 (0.001)	0.001 (0.001)	0.003 (0.002)	0.002 (0.001)	0.001 (0.001)	
0.6	0.16	15	0%	0.007 (0.010)	0.004 (0.005)	0.002 (0.003)	0.007 (0.010)	0.004 (0.005)	0.002 (0.003)	
			20%	0.010 (0.014)	0.005 (0.008)	0.003 (0.004)	0.008 (0.012)	0.004 (0.006)	0.003 (0.004)	
			40%	0.011 (0.017)	0.005 (0.008)	0.003 (0.005)	0.009 (0.013)	0.004 (0.007)	0.003 (0.004)	
		30	0%	0.004 (0.004)	0.002 (0.002)	0.001 (0.001)	0.004 (0.004)	0.002 (0.002)	0.001 (0.001)	
			20%	0.006 (0.006)	0.003 (0.003)	0.002 (0.002)	0.005 (0.005)	0.003 (0.002)	0.001 (0.001)	
			40%	0.006 (0.006)	0.003 (0.003)	0.002 (0.002)	0.005 (0.005)	0.003 (0.003)	0.001 (0.002)	
		60	0%	0.002 (0.002)	0.001 (0.001)	0.001 (0.001)	0.002 (0.002)	0.001 (0.001)	0.001 (0.001)	
			20%	0.002 (0.002)	0.002 (0.002)	0.001 (0.001)	0.002 (0.002)	0.002 (0.001)	0.001 (0.001)	
			40%	0.002 (0.003)	0.002 (0.002)	0.001 (0.001)	0.002 (0.002)	0.002 (0.001)	0.001 (0.001)	
		120	0%	0.001 (0.001)	0.001 (0.001)	0.001 (0.000)	0.001 (0.001)	0.001 (0.001)	0.001 (0.000)	
			20%	0.002 (0.002)	0.002 (0.001)	0.001 (0.001)	0.002 (0.001)	0.001 (0.001)	0.001 (0.001)	
			40%	0.003 (0.002)	0.002 (0.001)	0.001 (0.001)	0.002 (0.002)	0.001 (0.001)	0.001 (0.001)	
	0.64	15	0%	0.006 (0.008)	0.003 (0.004)	0.002 (0.003)	0.006 (0.008)	0.003 (0.004)	0.002 (0.003)	
			20%	0.012 (0.016)	0.006 (0.008)	0.004 (0.005)	0.008 (0.012)	0.004 (0.006)	0.003 (0.004)	
			40%	0.012 (0.018)	0.005 (0.008)	0.004 (0.005)	0.009 (0.013)	0.004 (0.007)	0.003 (0.004)	
		30	0%	0.003 (0.003)	0.002 (0.002)	0.001 (0.001)	0.003 (0.003)	0.002 (0.002)	0.001 (0.001)	
			20%	0.007 (0.006)	0.003 (0.003)	0.002 (0.002)	0.004 (0.004)	0.002 (0.002)	0.001 (0.001)	
			40%	0.006 (0.006)	0.004 (0.003)	0.002 (0.002)	0.005 (0.005)	0.003 (0.002)	0.002 (0.002)	
		60	0%	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)	
			20%	0.003 (0.003)	0.002 (0.002)	0.001 (0.001)	0.002 (0.002)	0.002 (0.001)	0.001 (0.001)	
			40%	0.003 (0.003)	0.002 (0.002)	0.001 (0.001)	0.003 (0.002)	0.002 (0.001)	0.001 (0.001)	
		120	0%	0.001 (0.001)	0.001 (0.001)	0.001 (0.000)	0.001 (0.001)	0.001 (0.001)	0.001 (0.000)	
			20%	0.002 (0.002)	0.002 (0.001)	0.001 (0.001)	0.002 (0.001)	0.001 (0.001)	0.001 (0.001)	
			40%	0.003 (0.002)	0.002 (0.001)	0.001 (0.001)	0.003 (0.002)	0.002 (0.001)	0.001 (0.001)	

Note: Population value for this parameter is 0. FE = Fixed Effect of Between-Time Random Slope; RE = Random Effect of Between-Time Random Slope; N = Sample Size; T = Measurement Occasions; PMD = Planned-Missing Data Percentage; ω = Reliability. The values outside the brackets represent the average point-estimate of the parameter across the successful replications. The values enclosed in the brackets represent the average standard deviation of the posterior distribution of the parameter across the successful replications.

Table 5.27: Descriptive Statistics for Random Effect of Random Intercept of M at Between-Time Level

FE	RE	T	PMD	$\omega = 0.60$			$\omega = 0.80$			
				50	N 100	200	50	N 100	200	
0.3	0.16	15	0%	0.010 (0.014)	0.005 (0.007)	0.003 (0.004)	$\sigma_{\xi_{M_t}}^2$	0.010 (0.014)	0.005 (0.007)	0.003 (0.004)
			20%	0.016 (0.021)	0.007 (0.010)	0.004 (0.005)		0.013 (0.017)	0.006 (0.009)	0.004 (0.004)
			40%	0.013 (0.017)	0.006 (0.009)	0.004 (0.004)		0.012 (0.016)	0.006 (0.008)	0.004 (0.004)
		30	0%	0.006 (0.006)	0.003 (0.003)	0.002 (0.002)		0.006 (0.006)	0.003 (0.003)	0.002 (0.002)
			20%	0.010 (0.009)	0.005 (0.005)	0.003 (0.002)		0.007 (0.007)	0.004 (0.004)	0.002 (0.002)
			40%	0.007 (0.008)	0.004 (0.004)	0.002 (0.002)		0.007 (0.007)	0.004 (0.003)	0.002 (0.002)
		60	0%	0.003 (0.003)	0.002 (0.002)	0.001 (0.001)		0.003 (0.003)	0.002 (0.002)	0.001 (0.001)
			20%	0.006 (0.005)	0.003 (0.002)	0.002 (0.001)		0.004 (0.004)	0.003 (0.002)	0.001 (0.001)
			40%	0.004 (0.004)	0.002 (0.002)	0.001 (0.001)		0.004 (0.004)	0.002 (0.002)	0.001 (0.001)
		120	0%	0.003 (0.002)	0.001 (0.001)	0.001 (0.001)		0.003 (0.002)	0.001 (0.001)	0.001 (0.001)
			20%	0.005 (0.003)	0.002 (0.001)	0.002 (0.001)		0.004 (0.002)	0.001 (0.001)	0.001 (0.001)
			40%	0.003 (0.002)	0.001 (0.001)	0.001 (0.001)		0.003 (0.002)	0.001 (0.001)	0.001 (0.001)
	0.64	15	0%	0.009 (0.012)	0.004 (0.006)	0.003 (0.003)	0.009 (0.012)	0.004 (0.006)	0.003 (0.003)	
			20%	0.017 (0.023)	0.008 (0.012)	0.005 (0.006)	0.013 (0.018)	0.006 (0.009)	0.003 (0.004)	
			40%	0.015 (0.020)	0.007 (0.010)	0.004 (0.005)	0.012 (0.017)	0.006 (0.009)	0.003 (0.004)	
		30	0%	0.004 (0.005)	0.003 (0.003)	0.002 (0.002)	0.004 (0.005)	0.003 (0.003)	0.002 (0.002)	
			20%	0.011 (0.010)	0.006 (0.005)	0.003 (0.003)	0.007 (0.007)	0.004 (0.004)	0.002 (0.002)	
			40%	0.008 (0.008)	0.005 (0.004)	0.002 (0.002)	0.007 (0.007)	0.003 (0.003)	0.002 (0.002)	
		60	0%	0.002 (0.003)	0.002 (0.001)	0.001 (0.001)	0.002 (0.003)	0.002 (0.001)	0.001 (0.001)	
			20%	0.008 (0.006)	0.004 (0.003)	0.002 (0.002)	0.005 (0.004)	0.003 (0.002)	0.002 (0.001)	
			40%	0.004 (0.004)	0.003 (0.002)	0.002 (0.001)	0.003 (0.003)	0.002 (0.002)	0.001 (0.001)	
		120	0%	0.002 (0.001)	0.001 (0.001)	0.001 (0.001)	0.002 (0.001)	0.001 (0.001)	0.001 (0.001)	
			20%	0.007 (0.003)	0.003 (0.002)	0.002 (0.001)	0.004 (0.002)	0.002 (0.001)	0.001 (0.001)	
			40%	0.004 (0.002)	0.001 (0.001)	0.001 (0.001)	0.003 (0.002)	0.001 (0.001)	0.001 (0.001)	
0.6	0.16	15	0%	0.010 (0.013)	0.005 (0.007)	0.003 (0.003)	0.010 (0.013)	0.005 (0.007)	0.003 (0.003)	
			20%	0.019 (0.024)	0.009 (0.012)	0.004 (0.005)	0.013 (0.018)	0.006 (0.009)	0.004 (0.004)	
			40%	0.012 (0.016)	0.005 (0.008)	0.003 (0.004)	0.011 (0.015)	0.005 (0.008)	0.003 (0.004)	
		30	0%	0.005 (0.005)	0.003 (0.003)	0.002 (0.002)	0.005 (0.005)	0.003 (0.003)	0.002 (0.002)	
			20%	0.010 (0.009)	0.006 (0.005)	0.003 (0.003)	0.007 (0.007)	0.004 (0.004)	0.002 (0.002)	
			40%	0.006 (0.006)	0.004 (0.003)	0.002 (0.002)	0.005 (0.006)	0.003 (0.003)	0.002 (0.002)	
		60	0%	0.003 (0.003)	0.002 (0.001)	0.001 (0.001)	0.003 (0.003)	0.002 (0.001)	0.001 (0.001)	
			20%	0.007 (0.005)	0.004 (0.003)	0.002 (0.002)	0.004 (0.004)	0.002 (0.002)	0.002 (0.001)	
			40%	0.004 (0.003)	0.002 (0.002)	0.002 (0.001)	0.003 (0.003)	0.002 (0.002)	0.001 (0.001)	
		120	0%	0.002 (0.001)	0.001 (0.001)	0.001 (0.001)	0.002 (0.001)	0.001 (0.001)	0.001 (0.001)	
			20%	0.006 (0.003)	0.003 (0.001)	0.002 (0.001)	0.004 (0.002)	0.001 (0.001)	0.001 (0.001)	
			40%	0.003 (0.002)	0.001 (0.001)	0.002 (0.001)	0.003 (0.002)	0.001 (0.001)	0.001 (0.001)	
	0.64	15	0%	0.008 (0.011)	0.004 (0.006)	0.003 (0.003)	0.008 (0.012)	0.004 (0.006)	0.003 (0.003)	
			20%	0.021 (0.027)	0.010 (0.014)	0.005 (0.006)	0.014 (0.019)	0.006 (0.010)	0.004 (0.005)	
			40%	0.014 (0.019)	0.006 (0.010)	0.004 (0.005)	0.010 (0.015)	0.005 (0.008)	0.003 (0.004)	
		30	0%	0.004 (0.004)	0.003 (0.002)	0.002 (0.001)	0.004 (0.004)	0.003 (0.002)	0.002 (0.001)	
			20%	0.014 (0.012)	0.007 (0.006)	0.003 (0.003)	0.008 (0.008)	0.004 (0.004)	0.003 (0.002)	
			40%	0.006 (0.007)	0.004 (0.004)	0.002 (0.002)	0.005 (0.006)	0.003 (0.003)	0.002 (0.002)	
		60	0%	0.002 (0.002)	0.001 (0.001)	0.001 (0.001)	0.002 (0.002)	0.001 (0.001)	0.001 (0.001)	
			20%	0.008 (0.006)	0.005 (0.003)	0.003 (0.002)	0.005 (0.004)	0.003 (0.002)	0.002 (0.001)	
			40%	0.004 (0.004)	0.002 (0.002)	0.001 (0.001)	0.003 (0.003)	0.002 (0.002)	0.001 (0.001)	
		120	0%	0.002 (0.001)	0.001 (0.001)	0.001 (0.001)	0.002 (0.001)	0.001 (0.001)	0.001 (0.001)	
			20%	0.007 (0.003)	0.004 (0.002)	0.002 (0.001)	0.004 (0.002)	0.002 (0.001)	0.002 (0.001)	
			40%	0.003 (0.002)	0.001 (0.001)	0.001 (0.001)	0.002 (0.002)	0.001 (0.001)	0.001 (0.001)	

Note: Population value for this parameter is 0. FE = Fixed Effect of Between-Time Random Slope; RE = Random Effect of Between-Time Random Slope; N = Sample Size; T = Measurement Occasions; PMD = Planned-Missing Data Percentage; ω = Reliability. The values outside the brackets represent the average point-estimate of the parameter across the successful replications. The values enclosed in the brackets represent the average standard deviation of the posterior distribution of the parameter across the successful replications.

Table 5.28: Descriptive Statistics for Random Effect of Random Intercept of Y at Between-Time Level

FE	RE	T	PMD	$\omega = 0.60$			$\omega = 0.80$		
				50	N 100	200	50	N 100	200
0.3	0.16	15	0%	0.010 (0.014)	0.005 (0.007)	0.003 (0.004)	0.010 (0.014)	0.005 (0.007)	0.003 (0.004)
			20%	0.016 (0.021)	0.007 (0.010)	0.004 (0.005)	0.013 (0.017)	0.006 (0.009)	0.004 (0.004)
			40%	0.013 (0.017)	0.006 (0.009)	0.004 (0.004)	0.012 (0.016)	0.006 (0.008)	0.004 (0.004)
		30	0%	0.006 (0.006)	0.003 (0.003)	0.002 (0.002)	0.006 (0.006)	0.003 (0.003)	0.002 (0.002)
			20%	0.010 (0.009)	0.005 (0.005)	0.003 (0.002)	0.007 (0.007)	0.004 (0.004)	0.002 (0.002)
			40%	0.007 (0.008)	0.004 (0.004)	0.002 (0.002)	0.007 (0.007)	0.004 (0.003)	0.002 (0.002)
		60	0%	0.003 (0.003)	0.002 (0.002)	0.001 (0.001)	0.003 (0.003)	0.002 (0.002)	0.001 (0.001)
			20%	0.006 (0.005)	0.003 (0.002)	0.002 (0.001)	0.004 (0.004)	0.003 (0.002)	0.001 (0.001)
			40%	0.004 (0.004)	0.002 (0.002)	0.001 (0.001)	0.004 (0.004)	0.002 (0.002)	0.001 (0.001)
		120	0%	0.003 (0.002)	0.001 (0.001)	0.001 (0.001)	0.003 (0.002)	0.001 (0.001)	0.001 (0.001)
			20%	0.005 (0.003)	0.002 (0.001)	0.002 (0.001)	0.004 (0.002)	0.001 (0.001)	0.001 (0.001)
			40%	0.003 (0.002)	0.001 (0.001)	0.001 (0.001)	0.003 (0.002)	0.001 (0.001)	0.001 (0.001)
	0.64	15	0%	0.009 (0.012)	0.004 (0.006)	0.003 (0.003)	0.009 (0.012)	0.004 (0.006)	0.003 (0.003)
			20%	0.017 (0.023)	0.008 (0.012)	0.005 (0.006)	0.013 (0.018)	0.006 (0.009)	0.003 (0.004)
			40%	0.015 (0.020)	0.007 (0.010)	0.004 (0.005)	0.012 (0.017)	0.006 (0.009)	0.003 (0.004)
		30	0%	0.004 (0.005)	0.003 (0.003)	0.002 (0.002)	0.004 (0.005)	0.003 (0.003)	0.002 (0.002)
			20%	0.011 (0.010)	0.006 (0.005)	0.003 (0.003)	0.007 (0.007)	0.004 (0.004)	0.002 (0.002)
			40%	0.008 (0.008)	0.005 (0.004)	0.002 (0.002)	0.007 (0.007)	0.003 (0.003)	0.002 (0.002)
		60	0%	0.002 (0.003)	0.002 (0.001)	0.001 (0.001)	0.002 (0.003)	0.002 (0.001)	0.001 (0.001)
			20%	0.008 (0.006)	0.004 (0.003)	0.002 (0.002)	0.005 (0.004)	0.003 (0.002)	0.002 (0.001)
			40%	0.004 (0.004)	0.003 (0.002)	0.002 (0.001)	0.003 (0.003)	0.002 (0.002)	0.001 (0.001)
		120	0%	0.002 (0.001)	0.001 (0.001)	0.001 (0.001)	0.002 (0.001)	0.001 (0.001)	0.001 (0.001)
			20%	0.007 (0.003)	0.003 (0.002)	0.002 (0.001)	0.004 (0.002)	0.002 (0.001)	0.001 (0.001)
			40%	0.004 (0.002)	0.001 (0.001)	0.001 (0.001)	0.003 (0.002)	0.001 (0.001)	0.001 (0.001)
0.6	0.16	15	0%	0.010 (0.013)	0.005 (0.007)	0.003 (0.003)	0.010 (0.013)	0.005 (0.007)	0.003 (0.003)
			20%	0.019 (0.024)	0.009 (0.012)	0.004 (0.005)	0.013 (0.018)	0.006 (0.009)	0.004 (0.004)
			40%	0.012 (0.016)	0.005 (0.008)	0.003 (0.004)	0.011 (0.015)	0.005 (0.008)	0.003 (0.004)
		30	0%	0.005 (0.005)	0.003 (0.003)	0.002 (0.002)	0.005 (0.005)	0.003 (0.003)	0.002 (0.002)
			20%	0.010 (0.009)	0.006 (0.005)	0.003 (0.003)	0.007 (0.007)	0.004 (0.004)	0.002 (0.002)
			40%	0.006 (0.006)	0.004 (0.003)	0.002 (0.002)	0.005 (0.006)	0.003 (0.003)	0.002 (0.002)
		60	0%	0.003 (0.003)	0.002 (0.001)	0.001 (0.001)	0.003 (0.003)	0.002 (0.001)	0.001 (0.001)
			20%	0.007 (0.005)	0.004 (0.003)	0.002 (0.002)	0.004 (0.004)	0.002 (0.002)	0.002 (0.001)
			40%	0.004 (0.003)	0.002 (0.002)	0.002 (0.001)	0.003 (0.003)	0.002 (0.002)	0.001 (0.001)
		120	0%	0.002 (0.001)	0.001 (0.001)	0.001 (0.001)	0.002 (0.001)	0.001 (0.001)	0.001 (0.001)
			20%	0.006 (0.003)	0.003 (0.001)	0.002 (0.001)	0.004 (0.002)	0.001 (0.001)	0.001 (0.001)
			40%	0.003 (0.002)	0.001 (0.001)	0.002 (0.001)	0.003 (0.002)	0.001 (0.001)	0.001 (0.001)
	0.64	15	0%	0.008 (0.011)	0.004 (0.006)	0.003 (0.003)	0.008 (0.012)	0.004 (0.006)	0.003 (0.003)
			20%	0.021 (0.027)	0.010 (0.014)	0.005 (0.006)	0.014 (0.019)	0.006 (0.010)	0.004 (0.005)
			40%	0.014 (0.019)	0.006 (0.010)	0.004 (0.005)	0.010 (0.015)	0.005 (0.008)	0.003 (0.004)
		30	0%	0.004 (0.004)	0.003 (0.002)	0.002 (0.001)	0.004 (0.004)	0.003 (0.002)	0.002 (0.001)
			20%	0.014 (0.012)	0.007 (0.006)	0.003 (0.003)	0.008 (0.008)	0.004 (0.004)	0.003 (0.002)
			40%	0.006 (0.007)	0.004 (0.004)	0.002 (0.002)	0.005 (0.006)	0.003 (0.003)	0.002 (0.002)
		60	0%	0.002 (0.002)	0.001 (0.001)	0.001 (0.001)	0.002 (0.002)	0.001 (0.001)	0.001 (0.001)
			20%	0.008 (0.006)	0.005 (0.003)	0.003 (0.002)	0.005 (0.004)	0.003 (0.002)	0.002 (0.001)
			40%	0.004 (0.004)	0.002 (0.002)	0.001 (0.001)	0.003 (0.003)	0.002 (0.002)	0.001 (0.001)
		120	0%	0.002 (0.001)	0.001 (0.001)	0.001 (0.001)	0.002 (0.001)	0.001 (0.001)	0.001 (0.001)
			20%	0.007 (0.003)	0.004 (0.002)	0.002 (0.001)	0.004 (0.002)	0.002 (0.001)	0.002 (0.001)
			40%	0.003 (0.002)	0.001 (0.001)	0.001 (0.001)	0.002 (0.002)	0.001 (0.001)	0.001 (0.001)

Note: Population value for this parameter is 0. FE = Fixed Effect of Between-Time Random Slope; RE = Random Effect of Between-Time Random Slope; N = Sample Size; T = Measurement Occasions; PMD = Planned-Missing Data Percentage; ω = Reliability. The values outside the brackets represent the average point-estimate of the parameter across the successful replications. The values enclosed in the brackets represent the average standard deviation of the posterior distribution of the parameter across the successful replications.

Table 5.29: Rejection of the Random Effect of Random Intercept of X at Between-Time Level

FE	RE	T	PMD	$\omega = 0.60$			$\sigma_{\xi_{Xt}}^2$	$\omega = 0.80$					
				50	N 100	200		50	N 100	200			
0.3	0.16	15	0%	0.000	0.000	0.000	0.000	0.000	0.000	0.000			
			20%	0.000	0.000	0.000		0.000	0.000	0.000			
			40%	0.000	0.000	0.000		0.000	0.000	0.000			
		30	0%	0.000	0.000	0.000		0.000	0.000	0.000	0.000		
			20%	0.000	0.000	0.000		0.000	0.000	0.000	0.000		
			40%	0.000	0.000	0.000		0.000	0.000	0.000	0.000		
		60	0%	0.000	0.000	0.000		0.000	0.000	0.000	0.000		
			20%	0.000	0.000	0.000		0.000	0.000	0.000	0.000		
			40%	0.000	0.000	0.000		0.000	0.000	0.000	0.000		
		120	0%	0.000	0.000	0.000		0.000	0.000	0.000	0.000		
			20%	0.000	0.000	0.000		0.000	0.000	0.000	0.000		
			40%	0.000	0.000	0.000		0.000	0.000	0.000	0.000		
	0.64	15	0%	0.000	0.000	0.000		0.000	0.000	0.000	0.000		
			20%	0.000	0.000	0.000		0.000	0.000	0.000	0.000		
			40%	0.000	0.000	0.000		0.000	0.000	0.000	0.000		
		30	0%	0.000	0.000	0.000		0.000	0.000	0.000	0.000		
			20%	0.002	0.000	0.000		0.000	0.000	0.000	0.000		
			40%	0.000	0.000	0.000		0.000	0.000	0.000	0.000		
		60	0%	0.000	0.000	0.000		0.000	0.000	0.000	0.000		
			20%	0.000	0.000	0.000		0.000	0.000	0.000	0.000		
			40%	0.002	0.000	0.000		0.000	0.000	0.000	0.000		
		120	0%	0.000	0.000	0.000		0.000	0.000	0.000	0.000		
			20%	0.000	0.000	0.000		0.000	0.000	0.000	0.000		
			40%	0.000	0.000	0.000		0.000	0.000	0.000	0.000		
	0.6	0.16	15	0%	0.000	0.000		0.000	0.000	0.000	0.000	0.000	
				20%	0.000	0.000		0.000		0.000	0.000	0.000	
				40%	0.000	0.000		0.000		0.000	0.000	0.000	
			30	0%	0.000	0.000		0.000		0.000	0.000	0.000	0.000
				20%	0.000	0.000		0.000		0.000	0.000	0.000	0.000
				40%	0.000	0.000		0.000		0.000	0.000	0.000	0.000
			60	0%	0.000	0.000		0.000		0.000	0.000	0.000	0.000
				20%	0.000	0.000		0.000		0.000	0.000	0.000	0.000
				40%	0.000	0.000		0.000		0.000	0.000	0.000	0.000
			120	0%	0.000	0.000		0.000		0.000	0.000	0.000	0.000
				20%	0.000	0.000		0.000		0.000	0.000	0.000	0.000
				40%	0.000	0.000		0.000		0.000	0.000	0.000	0.000
0.64		15	0%	0.000	0.000	0.000	0.000	0.000		0.000	0.000		
			20%	0.000	0.000	0.000	0.000	0.000		0.000	0.000		
			40%	0.000	0.000	0.000	0.000	0.000		0.000	0.000		
		30	0%	0.000	0.000	0.000	0.000	0.000		0.000	0.000		
			20%	0.000	0.000	0.000	0.000	0.000		0.000	0.000		
			40%	0.000	0.000	0.000	0.000	0.000		0.000	0.000		
		60	0%	0.000	0.000	0.000	0.000	0.000		0.000	0.000		
			20%	0.000	0.000	0.000	0.000	0.000		0.000	0.000		
			40%	0.000	0.000	0.000	0.000	0.000		0.000	0.000		
		120	0%	0.000	0.000	0.000	0.000	0.000		0.000	0.000		
			20%	0.000	0.000	0.000	0.000	0.000		0.000	0.000		
			40%	0.000	0.000	0.000	0.000	0.000		0.000	0.000		

Note: Population value for this parameter is 0. FE = Fixed Effect of Between-Time Random Slope; RE = Random Effect of Between-Time Random Slope; N = Sample Size; T = Measurement Occasions; PMD = Planned-Missing Data Percentage; ω = Reliability. The values represent the rejection averaged across successful replications. Values that were larger than the acceptable upper boundary of rejection (i.e., 0.20) were in bold.

Table 5.30: Rejection of the Random Effect of Random Intercept of M at Between-Time Level

FE	RE	T	PMD	$\omega = 0.60$			$\omega = 0.80$			
				50	100	200	50	100	200	
0.3	0.16	15	0%	0.000	0.000	0.000	0.000	0.000	0.000	
			20%	0.000	0.000	0.000	0.000	0.000	0.000	
			40%	0.000	0.000	0.000	0.000	0.000	0.000	
		30	0%	0.000	0.000	0.000	0.000	0.000	0.000	
			20%	0.000	0.000	0.000	0.000	0.000	0.000	
			40%	0.000	0.000	0.000	0.000	0.000	0.000	
		60	0%	0.000	0.000	0.000	0.000	0.000	0.000	
			20%	0.000	0.000	0.000	0.000	0.000	0.000	
			40%	0.000	0.000	0.000	0.000	0.000	0.000	
		120	0%	0.000	0.000	0.000	0.000	0.000	0.000	
			20%	0.000	0.000	0.000	0.000	0.000	0.000	
			40%	0.000	0.000	0.000	0.000	0.000	0.000	
	0.64	15	0%	0.000	0.000	0.000	0.000	0.000	0.000	
			20%	0.000	0.000	0.000	0.000	0.000	0.000	
			40%	0.000	0.000	0.000	0.000	0.000	0.000	
		30	0%	0.000	0.000	0.000	0.000	0.000	0.000	
			20%	0.002	0.000	0.000	0.000	0.000	0.000	
			40%	0.000	0.000	0.000	0.000	0.000	0.000	
		60	0%	0.000	0.000	0.000	0.000	0.000	0.000	
			20%	0.000	0.000	0.000	0.000	0.000	0.000	
			40%	0.002	0.000	0.000	0.000	0.000	0.000	
		120	0%	0.000	0.000	0.000	0.000	0.000	0.000	
			20%	0.002	0.000	0.000	0.000	0.000	0.000	
			40%	0.000	0.000	0.000	0.000	0.000	0.000	
	0.6	0.16	15	0%	0.000	0.000	0.000	0.000	0.000	0.000
				20%	0.000	0.000	0.000	0.000	0.000	0.000
				40%	0.000	0.000	0.000	0.000	0.000	0.000
			30	0%	0.000	0.000	0.000	0.000	0.000	0.000
				20%	0.000	0.000	0.000	0.000	0.000	0.000
				40%	0.000	0.000	0.000	0.000	0.000	0.000
			60	0%	0.000	0.000	0.000	0.000	0.000	0.000
				20%	0.000	0.000	0.000	0.000	0.000	0.000
				40%	0.000	0.000	0.000	0.000	0.000	0.000
			120	0%	0.000	0.000	0.000	0.000	0.000	0.000
				20%	0.000	0.000	0.000	0.000	0.000	0.000
				40%	0.000	0.000	0.000	0.000	0.000	0.000
0.64		15	0%	0.000	0.000	0.000	0.000	0.000	0.000	
			20%	0.002	0.000	0.000	0.000	0.000	0.000	
			40%	0.000	0.000	0.000	0.000	0.000	0.000	
		30	0%	0.000	0.000	0.000	0.000	0.000	0.000	
			20%	0.004	0.000	0.000	0.000	0.000	0.000	
			40%	0.000	0.000	0.000	0.000	0.000	0.000	
		60	0%	0.000	0.000	0.000	0.000	0.000	0.000	
			20%	0.000	0.000	0.000	0.000	0.000	0.000	
			40%	0.000	0.000	0.000	0.000	0.000	0.000	
		120	0%	0.000	0.000	0.000	0.000	0.000	0.000	
			20%	0.000	0.000	0.000	0.000	0.000	0.000	
			40%	0.000	0.000	0.000	0.000	0.000	0.000	

Note: Population value for this parameter is 0. FE = Fixed Effect of Between-Time Random Slope; RE = Random Effect of Between-Time Random Slope; N = Sample Size; T = Measurement Occasions; PMD = Planned-Missing Data Percentage; ω = Reliability. The values represent the rejection averaged across successful replications. Values that were larger than the acceptable upper boundary of rejection (i.e., 0.20) were in bold.

Table 5.31: Rejection of the Random Effect of Random Intercept of Y at Between-Time Level

FE	RE	T	PMD	$\omega = 0.60$			$\sigma_{\xi_i}^2$	$\omega = 0.80$		
				50	N 100	200		50	N 100	200
0.3	0.16	15	0%	0.000	0.000	0.000	0.000	0.000	0.000	0.000
			20%	0.000	0.000	0.000		0.000	0.000	0.000
			40%	0.000	0.000	0.000		0.000	0.000	0.000
		30	0%	0.000	0.000	0.000		0.000	0.000	0.000
			20%	0.000	0.000	0.000		0.000	0.000	0.000
			40%	0.000	0.000	0.000		0.000	0.000	0.000
		60	0%	0.000	0.000	0.000		0.000	0.000	0.000
			20%	0.000	0.000	0.000		0.000	0.000	0.000
			40%	0.000	0.000	0.000		0.000	0.000	0.000
		120	0%	0.000	0.000	0.000		0.000	0.000	0.000
			20%	0.000	0.000	0.000		0.000	0.000	0.000
			40%	0.000	0.000	0.000		0.000	0.000	0.000
	0.64	15	0%	0.000	0.000	0.000		0.000	0.000	0.000
			20%	0.000	0.000	0.000		0.000	0.000	0.000
			40%	0.000	0.000	0.000		0.000	0.000	0.000
		30	0%	0.000	0.000	0.000		0.000	0.000	0.000
			20%	0.002	0.000	0.000		0.000	0.000	0.000
			40%	0.000	0.000	0.000		0.000	0.000	0.000
		60	0%	0.000	0.000	0.000		0.000	0.000	0.000
			20%	0.000	0.000	0.000		0.000	0.000	0.000
			40%	0.002	0.000	0.000		0.000	0.000	0.000
		120	0%	0.000	0.000	0.000		0.000	0.000	0.000
			20%	0.000	0.000	0.000		0.000	0.000	0.000
			40%	0.000	0.000	0.000		0.000	0.000	0.000
0.6	0.16	15	0%	0.000	0.000	0.000	0.000	0.000	0.000	0.000
			20%	0.000	0.000	0.000		0.000	0.000	0.000
			40%	0.000	0.000	0.000		0.000	0.000	0.000
		30	0%	0.000	0.000	0.000		0.000	0.000	0.000
			20%	0.000	0.000	0.000		0.000	0.000	0.000
			40%	0.000	0.000	0.000		0.000	0.000	0.000
		60	0%	0.000	0.000	0.000		0.000	0.000	0.000
			20%	0.000	0.000	0.000		0.000	0.000	0.000
			40%	0.000	0.000	0.000		0.000	0.000	0.000
		120	0%	0.000	0.000	0.000		0.000	0.000	0.000
			20%	0.000	0.000	0.000		0.000	0.000	0.000
			40%	0.000	0.000	0.000		0.000	0.000	0.000
	0.64	15	0%	0.000	0.000	0.000		0.000	0.000	0.000
			20%	0.000	0.000	0.000		0.000	0.000	0.000
			40%	0.000	0.000	0.000		0.000	0.000	0.000
		30	0%	0.000	0.000	0.000		0.000	0.000	0.000
			20%	0.002	0.000	0.000		0.000	0.000	0.000
			40%	0.000	0.000	0.000		0.000	0.000	0.000
		60	0%	0.000	0.000	0.000		0.000	0.000	0.000
			20%	0.000	0.000	0.000		0.000	0.000	0.000
			40%	0.000	0.000	0.000		0.000	0.000	0.000
		120	0%	0.000	0.000	0.000		0.000	0.000	0.000
			20%	0.000	0.000	0.000		0.000	0.000	0.000
			40%	0.000	0.000	0.000		0.000	0.000	0.000

Note: Population value for this parameter is 0. FE = Fixed Effect of Between-Time Random Slope; RE = Random Effect of Between-Time Random Slope; N = Sample Size; T = Measurement Occasions; PMD = Planned-Missing Data Percentage; ω = Reliability. The values represent the rejection averaged across successful replications. Values that were larger than the acceptable upper boundary of rejection (i.e., 0.20) were in bold.

5.4.4 Random Slope at Between-Individual Level

Random Effect ($\sigma_{\xi\alpha_i}^2, \sigma_{\xi\beta_i}^2, \sigma_{\xi\tau_i}^2$)

The random effect (variance) of the random slope at the between-individual level was simulated with a population value of 0 (i.e., absence of individual-varying slope; see Table 5.32, Table 5.33, and Table 5.34 for the descriptive statistics). The tables contained the average parameter estimate over successful replication for the random effect of the random slopes at the between-individual level. These parameters represented the *variance* of the random variables at the between-individual level in Figure 5.3.2. The values in the parenthesis contained the average of the standard deviation of the parameter posterior distribution over successful replications.

The effect of the experimental factors on the parameter estimates seemed to depend on the specific parameter. For $\sigma_{\xi\alpha_i}^2$, large magnitude of over-estimation occurred at the $FE = 0.60$ paired with the $\omega = 0.60$, $PMD = 40\%$, and $T = 15, 30$, and 60 conditions. The standard deviation of the posterior distribution for these over-estimated parameters were also sizeable. For $\sigma_{\xi\beta_i}^2$, the over-estimation extended to the $\omega = 0.80$ conditions with almost all conditions under $FE = 0.60$ being over-estimated with large standard deviation of the posterior distribution. For $\sigma_{\xi\tau_i}^2$, a substantial over-estimation only occurred generally at $FE = 0.60$ and $RE = 0.16$ conditions. In general, for those conditions with presence of extreme over-estimation, the condition with higher reliability $\omega = 0.80$ would result in a lower bias than $\omega = 0.60$.

Rejection Note that rejection in the study was defined as the averaged number of 90% HDI for a specific parameter that *do not* contain the ROPE. Hence a lower rejection for the random effect (variance) of the random slope at the between-individual level was desirable because the simulation population value for the variance was 0. The rejection for each of the three parameters were presented in Table 5.35, Table 5.36, and Table 5.37.

Across the three tables, the conditions with higher reliability $\omega = 0.80$ would result in a lower rejection value than $\omega = 0.60$ in general. In contrast, a larger sample size N

would lead to slightly worse larger rejection value. However, similar to the observation of the parameter over-estimation, the effect of the simulation conditions on the rejection seemed to also depend on the specific parameter. Unlike the $\sigma_{\xi_{\tau_i}}^2$ parameter which showed rejection rate that were within the acceptable range (i.e., below 0.20), there were some conditions in which the $\sigma_{\xi_{\alpha_i}}^2$ parameter may suffer with rejection that were outside of the acceptable range (e.g. $PMD = 20\%$ at $\omega = 0.60$ and $FE = 0.60$ and $RE = 0.64$), while $\sigma_{\xi_{\beta_i}}^2$ had unacceptable rejection at $PMD = 0\%$ and 40% at both $\omega = 0.60$ and 0.80 for the $FE = 0.60$ and $RE = 0.16$ conditions.

Table 5.32: Descriptive Statistics for Random Effect of Random Slope α at Between-Individual Level

FE	RE	T	PMD	$\omega = 0.60$			$\omega = 0.80$		
				50	N 100	200	50	N 100	200
				$\sigma_{\xi_{\alpha_i}}^2$					
0.3	0.16	15	0%	0.019 (0.017)	0.012 (0.009)	0.007 (0.007)	0.019 (0.017)	0.011 (0.009)	0.007 (0.007)
			20%	0.027 (0.021)	0.019 (0.012)	0.016 (0.010)	0.022 (0.019)	0.013 (0.010)	0.009 (0.008)
			40%	0.029 (0.020)	0.021 (0.011)	0.019 (0.008)	0.024 (0.019)	0.016 (0.010)	0.012 (0.008)
		30	0%	0.009 (0.007)	0.005 (0.004)	0.004 (0.003)	0.009 (0.007)	0.005 (0.004)	0.004 (0.003)
			20%	0.019 (0.011)	0.016 (0.007)	0.016 (0.005)	0.011 (0.009)	0.007 (0.005)	0.007 (0.004)
			40%	0.021 (0.011)	0.018 (0.007)	0.018 (0.005)	0.014 (0.009)	0.011 (0.006)	0.010 (0.004)
		60	0%	0.003 (0.004)	0.004 (0.002)	0.002 (0.001)	0.003 (0.004)	0.004 (0.002)	0.002 (0.001)
			20%	0.016 (0.008)	0.016 (0.005)	0.015 (0.003)	0.006 (0.005)	0.006 (0.003)	0.004 (0.002)
			40%	0.018 (0.007)	0.017 (0.005)	0.016 (0.003)	0.009 (0.006)	0.010 (0.004)	0.009 (0.002)
		120	0%	0.002 (0.002)	0.002 (0.001)	0.001 (0.001)	0.002 (0.002)	0.002 (0.001)	0.001 (0.001)
			20%	0.017 (0.006)	0.015 (0.004)	0.016 (0.002)	0.006 (0.003)	0.005 (0.002)	0.005 (0.001)
			40%	0.017 (0.005)	0.016 (0.003)	0.016 (0.002)	0.009 (0.004)	0.009 (0.002)	0.009 (0.002)
0.64	0.64	15	0%	0.019 (0.017)	0.011 (0.009)	0.007 (0.007)	0.019 (0.017)	0.011 (0.009)	0.007 (0.007)
			20%	0.035 (0.025)	0.027 (0.014)	0.024 (0.011)	0.025 (0.020)	0.017 (0.011)	0.013 (0.009)
			40%	0.031 (0.020)	0.023 (0.011)	0.022 (0.009)	0.027 (0.020)	0.019 (0.011)	0.016 (0.009)
		30	0%	0.008 (0.007)	0.005 (0.004)	0.004 (0.003)	0.008 (0.007)	0.005 (0.004)	0.004 (0.003)
			20%	0.030 (0.015)	0.026 (0.009)	0.026 (0.007)	0.015 (0.010)	0.011 (0.006)	0.011 (0.005)
			40%	0.024 (0.012)	0.021 (0.007)	0.021 (0.005)	0.018 (0.010)	0.015 (0.007)	0.015 (0.005)
		60	0%	0.003 (0.004)	0.003 (0.002)	0.002 (0.001)	0.003 (0.004)	0.003 (0.002)	0.002 (0.001)
			20%	0.028 (0.011)	0.027 (0.007)	0.026 (0.005)	0.011 (0.006)	0.011 (0.004)	0.009 (0.003)
			40%	0.021 (0.008)	0.020 (0.005)	0.019 (0.003)	0.015 (0.007)	0.014 (0.004)	0.013 (0.003)
		120	0%	0.002 (0.002)	0.002 (0.001)	0.001 (0.001)	0.002 (0.002)	0.002 (0.001)	0.001 (0.001)
			20%	0.028 (0.008)	0.027 (0.006)	0.026 (0.004)	0.010 (0.004)	0.010 (0.003)	0.010 (0.002)
			40%	0.021 (0.006)	0.020 (0.004)	0.019 (0.003)	0.014 (0.005)	0.013 (0.003)	0.013 (0.002)
0.6	0.16	15	0%	0.020 (0.018)	0.013 (0.010)	0.008 (0.007)	0.019 (0.018)	0.012 (0.010)	0.008 (0.007)
			20%	0.049 (0.030)	0.037 (0.017)	0.036 (0.013)	0.029 (0.023)	0.020 (0.013)	0.015 (0.010)
			40%	0.021 (0.016)	111.000 (50.500)	234.000 (104.000)	0.021 (0.017)	0.014 (0.009)	0.011 (0.007)
		30	0%	0.008 (0.007)	0.006 (0.004)	0.004 (0.003)	0.008 (0.007)	0.005 (0.004)	0.004 (0.003)
			20%	0.042 (0.018)	0.039 (0.012)	0.039 (0.008)	0.018 (0.011)	0.015 (0.007)	0.015 (0.005)
			40%	24.700 (13.900)	20.500 (9.760)	15.700 (7.230)	0.010 (0.008)	0.008 (0.005)	0.008 (0.004)
		60	0%	0.003 (0.004)	0.004 (0.002)	0.002 (0.001)	0.003 (0.004)	0.004 (0.002)	0.002 (0.001)
			20%	0.042 (0.014)	0.040 (0.009)	0.039 (0.006)	0.014 (0.008)	0.015 (0.005)	0.013 (0.003)
			40%	3.290 (1.900)	4.050 (2.070)	1.570 (0.786)	0.007 (0.005)	0.007 (0.003)	0.006 (0.002)
		120	0%	0.002 (0.002)	0.002 (0.001)	0.001 (0.001)	0.002 (0.002)	0.002 (0.001)	0.001 (0.001)
			20%	0.042 (0.012)	0.038 (0.007)	0.038 (0.005)	0.015 (0.006)	0.014 (0.003)	0.013 (0.002)
			40%	0.008 (0.003)	0.103 (0.066)	0.008 (0.001)	0.005 (0.003)	0.006 (0.002)	0.005 (0.001)
0.64	0.64	15	0%	0.019 (0.017)	0.011 (0.009)	0.007 (0.007)	0.019 (0.017)	0.011 (0.009)	0.007 (0.007)
			20%	0.060 (0.035)	0.052 (0.021)	0.049 (0.016)	0.037 (0.026)	0.027 (0.015)	0.024 (0.012)
			40%	0.019 (0.015)	0.014 (0.008)	26.900 (11.700)	0.021 (0.017)	0.014 (0.009)	0.010 (0.007)
		30	0%	0.008 (0.007)	0.005 (0.004)	0.004 (0.003)	0.008 (0.007)	0.005 (0.004)	0.004 (0.003)
			20%	0.059 (0.023)	0.054 (0.015)	0.053 (0.010)	0.027 (0.014)	0.025 (0.009)	0.025 (0.007)
			40%	0.012 (0.008)	1.250 (0.563)	0.655 (0.297)	0.012 (0.008)	0.009 (0.005)	0.009 (0.004)
		60	0%	0.003 (0.004)	0.003 (0.002)	0.002 (0.001)	0.003 (0.004)	0.003 (0.002)	0.002 (0.001)
			20%	0.061 (0.019)	0.057 (0.012)	0.055 (0.008)	0.026 (0.011)	0.024 (0.007)	0.023 (0.004)
			40%	0.166 (0.083)	0.771 (0.394)	0.840 (0.440)	0.008 (0.005)	0.008 (0.003)	0.007 (0.002)
		120	0%	0.002 (0.002)	0.001 (0.001)	0.001 (0.001)	0.002 (0.002)	0.001 (0.001)	0.001 (0.001)
			20%	0.061 (0.016)	0.058 (0.010)	0.059 (0.007)	0.025 (0.008)	0.024 (0.005)	0.025 (0.004)
			40%	0.010 (0.004)	0.080 (0.033)	0.091 (0.032)	0.008 (0.003)	0.007 (0.002)	0.007 (0.001)

Note: Population value for this parameter is 0. FE = Fixed Effect of Between-Time Random Slope; RE = Random Effect of Between-Time Random Slope; N = Sample Size; T = Measurement Occasions; PMD = Planned-Missing Data Percentage; ω = Reliability. The values outside the brackets represent the average point-estimate of the parameter across the successful replications. The values enclosed in the brackets represent the average standard deviation of the posterior distribution of the parameter across the successful replications.

Table 5.33: Descriptive Statistics for Random Effect of Random Slope β at Between-Individual Level

FE	RE	T	PMD	$\omega = 0.60$			$\sigma_{\epsilon_{pi}}^2$	$\omega = 0.80$		
				50	N 100	200		50	N 100	200
0.3	0.16	15	0%	0.015 (0.014)	0.010 (0.009)	0.004 (0.006)	0.015 (0.014)	0.010 (0.008)	0.004 (0.005)	
			20%	0.015 (0.014)	0.010 (0.008)	0.004 (0.005)		0.010 (0.009)	0.004 (0.005)	
			40%	0.028 (0.019)	0.022 (0.012)	0.019 (0.009)		0.020 (0.017)	0.015 (0.010)	0.010 (0.007)
			40%	0.007 (0.006)	0.004 (0.004)	0.003 (0.003)		0.007 (0.006)	0.004 (0.004)	0.003 (0.003)
		30	0%	0.008 (0.007)	0.005 (0.004)	0.005 (0.003)		0.008 (0.007)	0.005 (0.004)	0.004 (0.003)
			20%	0.022 (0.011)	0.019 (0.007)	0.018 (0.005)		0.014 (0.009)	0.010 (0.006)	0.010 (0.004)
			40%	0.004 (0.003)	0.003 (0.002)	0.002 (0.001)		0.004 (0.003)	0.003 (0.002)	0.002 (0.001)
			40%	0.005 (0.004)	0.004 (0.002)	0.003 (0.002)		0.005 (0.004)	0.003 (0.002)	0.002 (0.001)
		60	0%	0.018 (0.007)	0.017 (0.005)	0.017 (0.003)		0.010 (0.005)	0.009 (0.003)	0.009 (0.002)
			20%	0.001 (0.002)	0.001 (0.001)	0.001 (0.001)		0.001 (0.002)	0.001 (0.001)	0.001 (0.001)
			40%	0.003 (0.002)	0.003 (0.002)	0.003 (0.001)		0.002 (0.002)	0.002 (0.001)	0.002 (0.001)
			40%	0.017 (0.005)	0.016 (0.003)	0.016 (0.002)		0.009 (0.004)	0.008 (0.002)	0.008 (0.002)
	0.64	15	0%	0.011 (0.011)	0.007 (0.006)	0.003 (0.004)	0.011 (0.011)	0.007 (0.006)	0.003 (0.004)	
			20%	0.014 (0.012)	0.009 (0.007)	0.004 (0.005)	0.013 (0.012)	0.008 (0.007)	0.003 (0.005)	
			40%	0.023 (0.017)	0.019 (0.011)	35.600 (15.700)	0.019 (0.015)	0.014 (0.009)	0.009 (0.007)	
			40%	0.006 (0.005)	0.003 (0.003)	0.003 (0.002)	0.006 (0.005)	0.003 (0.003)	0.003 (0.002)	
		30	0%	0.008 (0.006)	0.005 (0.004)	0.004 (0.003)	0.007 (0.006)	0.004 (0.003)	0.003 (0.002)	
			20%	0.019 (0.010)	0.017 (0.007)	1.640 (0.759)	0.013 (0.008)	0.010 (0.005)	0.010 (0.004)	
			40%	0.003 (0.003)	0.002 (0.001)	0.001 (0.001)	0.003 (0.003)	0.002 (0.001)	0.001 (0.001)	
			40%	0.004 (0.003)	0.003 (0.002)	0.002 (0.001)	0.004 (0.003)	0.003 (0.002)	0.002 (0.001)	
		60	0%	0.017 (0.007)	0.016 (0.004)	0.015 (0.003)	0.011 (0.005)	0.009 (0.003)	0.009 (0.002)	
			20%	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)	
			40%	0.002 (0.002)	0.002 (0.001)	0.002 (0.001)	0.002 (0.002)	0.002 (0.001)	0.002 (0.001)	
			40%	0.015 (0.005)	0.015 (0.003)	0.014 (0.002)	0.009 (0.003)	0.009 (0.002)	0.009 (0.001)	
0.6	0.16	15	0%	1849.000 (891.000)	1197.000 (533.000)	5449.000 (2351.000)	279.000 (132.000)	488.000 (216.000)	2304.000 (996.000)	
			20%	0.016 (0.014)	0.011 (0.008)	0.006 (0.005)	0.015 (0.014)	40.300 (17.700)	228.000 (99.800)	
			40%	3100.000 (1482.000)	2379.000 (1068.000)	7000.000 (3014.000)	636.000 (302.000)	811.000 (365.000)	3464.000 (1496.000)	
			40%	956.000 (466.000)	1716.000 (776.000)	1946.000 (803.000)	470.000 (229.000)	1231.000 (561.000)	1271.000 (528.000)	
		30	0%	0.008 (0.006)	29.800 (14.000)	10.700 (4.610)	7.980 (3.990)	208.000 (95.500)	95.700 (40.200)	
			20%	1903.000 (935.000)	1984.000 (902.000)	2404.000 (993.000)	1303.000 (641.000)	1664.000 (761.000)	2027.000 (843.000)	
			40%	52.600 (27.100)	511.000 (233.000)	318.000 (138.000)	25.300 (13.000)	373.000 (171.000)	215.000 (93.500)	
			40%	0.006 (0.004)	0.005 (0.002)	1.040 (0.491)	0.005 (0.003)	24.900 (11.800)	6.510 (2.970)	
		60	0%	367.000 (189.000)	578.000 (261.000)	572.000 (244.000)	119.000 (61.400)	542.000 (248.000)	457.000 (198.000)	
			20%	0.001 (0.001)	58.900 (29.400)	73.100 (36.000)	0.001 (0.001)	42.500 (21.200)	58.600 (29.000)	
			40%	0.004 (0.002)	0.004 (0.001)	0.004 (0.001)	0.003 (0.002)	0.304 (0.153)	0.487 (0.258)	
			40%	283.000 (143.000)	124.000 (59.200)	139.000 (65.100)	157.000 (81.000)	118.000 (57.800)	134.000 (64.900)	
	0.64	15	0%	139.000 (65.400)	104.000 (45.700)	512.000 (223.000)	60.800 (29.000)	100.000 (43.400)	335.000 (146.000)	
			20%	7.810 (3.740)	0.009 (0.007)	37.700 (16.400)	5.420 (2.600)	8.460 (3.890)	91.900 (40.500)	
			40%	366.000 (173.000)	387.000 (174.000)	1826.000 (790.000)	192.000 (91.200)	133.000 (60.400)	814.000 (355.000)	
			40%	8.070 (4.070)	46.800 (22.400)	43.300 (19.000)	0.005 (0.004)	35.500 (17.100)	34.200 (15.000)	
		30	0%	0.008 (0.006)	0.005 (0.003)	0.004 (0.002)	0.007 (0.005)	12.900 (6.440)	3.380 (1.480)	
			20%	108.000 (53.200)	346.000 (162.000)	401.000 (169.000)	21.200 (10.600)	126.000 (60.300)	111.000 (47.400)	
			40%	0.003 (0.002)	2.020 (0.972)	0.394 (0.192)	0.003 (0.002)	1.760 (0.871)	0.306 (0.164)	
			40%	0.005 (0.003)	0.004 (0.002)	0.003 (0.001)	0.004 (0.003)	0.003 (0.002)	0.003 (0.001)	
		60	0%	4.130 (2.170)	58.200 (27.600)	47.400 (21.200)	0.008 (0.004)	15.200 (7.400)	2.890 (1.300)	
			20%	0.001 (0.001)	0.001 (0.001)	0.001 (0.000)	0.001 (0.002)	0.001 (0.001)	0.001 (0.000)	
			40%	0.003 (0.002)	0.003 (0.001)	0.003 (0.001)	0.003 (0.002)	0.002 (0.001)	0.003 (0.001)	
			40%	0.010 (0.004)	2.310 (1.100)	3.930 (2.010)	0.007 (0.003)	0.147 (0.073)	0.232 (0.130)	

Note: Population value for this parameter is 0. FE = Fixed Effect of Between-Time Random Slope; RE = Random Effect of Between-Time Random Slope; N = Sample Size; T = Measurement Occasions; PMD = Planned-Missing Data Percentage; ω = Reliability. The values outside the brackets represent the average point-estimate of the parameter across the successful replications. The values enclosed in the brackets represent the average standard deviation of the posterior distribution of the parameter across the successful replications.

Table 5.34: Descriptive Statistics for Random Effect of Random Slope τ at Between-Individual Level

FE	RE	T	PMD	$\omega = 0.60$			$\omega = 0.80$		
				50	N 100	200	50	N 100	200
0.3	0.16	15	0%	0.021 (0.018)	0.013 (0.011)	0.008 (0.006)	0.021 (0.018)	0.013 (0.011)	0.008 (0.006)
			20%	0.029 (0.021)	0.022 (0.014)	0.018 (0.009)	0.023 (0.019)	0.016 (0.012)	0.011 (0.007)
			40%	0.022 (0.017)	0.014 (0.010)	0.009 (0.006)	0.022 (0.018)	0.014 (0.011)	0.009 (0.006)
		30	0%	0.008 (0.008)	0.005 (0.004)	0.004 (0.003)	0.008 (0.008)	0.005 (0.004)	0.004 (0.003)
			20%	0.018 (0.012)	0.016 (0.007)	0.016 (0.005)	0.011 (0.010)	0.008 (0.005)	0.007 (0.004)
			40%	0.011 (0.009)	0.009 (0.005)	0.007 (0.004)	0.010 (0.009)	0.007 (0.005)	0.006 (0.003)
		60	0%	0.004 (0.004)	0.003 (0.002)	0.002 (0.002)	0.004 (0.004)	0.003 (0.002)	0.002 (0.002)
			20%	0.016 (0.007)	0.016 (0.005)	0.015 (0.003)	0.008 (0.005)	0.007 (0.003)	0.006 (0.002)
			40%	0.009 (0.005)	0.008 (0.003)	0.007 (0.002)	0.007 (0.005)	0.006 (0.003)	0.005 (0.002)
		120	0%	0.002 (0.002)	0.002 (0.001)	0.001 (0.001)	0.002 (0.002)	0.002 (0.001)	0.001 (0.001)
			20%	0.016 (0.005)	0.015 (0.003)	0.015 (0.002)	0.007 (0.003)	0.006 (0.002)	0.006 (0.001)
			40%	0.008 (0.003)	0.007 (0.002)	0.007 (0.001)	0.005 (0.003)	0.004 (0.002)	0.004 (0.001)
	0.64	15	0%	0.021 (0.019)	0.013 (0.011)	0.008 (0.006)	0.021 (0.018)	0.013 (0.011)	0.008 (0.006)
			20%	0.036 (0.025)	0.026 (0.015)	0.022 (0.010)	0.029 (0.022)	0.020 (0.014)	0.015 (0.008)
			40%	0.024 (0.019)	0.016 (0.011)	0.011 (0.007)	0.026 (0.021)	0.016 (0.012)	0.011 (0.007)
		30	0%	0.008 (0.008)	0.005 (0.004)	0.004 (0.003)	0.008 (0.008)	0.005 (0.004)	0.004 (0.003)
			20%	0.026 (0.015)	0.022 (0.009)	0.021 (0.006)	0.016 (0.012)	0.012 (0.007)	0.012 (0.005)
			40%	0.013 (0.010)	0.009 (0.006)	0.008 (0.004)	0.012 (0.010)	0.009 (0.006)	0.008 (0.004)
		60	0%	0.004 (0.004)	0.003 (0.002)	0.002 (0.002)	0.004 (0.004)	0.003 (0.002)	0.002 (0.002)
			20%	0.023 (0.009)	0.022 (0.006)	0.021 (0.004)	0.013 (0.007)	0.012 (0.005)	0.011 (0.003)
			40%	0.010 (0.006)	0.009 (0.004)	0.008 (0.003)	0.009 (0.006)	0.008 (0.004)	0.006 (0.003)
		120	0%	0.003 (0.002)	0.002 (0.001)	0.001 (0.001)	0.003 (0.002)	0.002 (0.001)	0.001 (0.001)
			20%	0.022 (0.007)	0.022 (0.005)	0.021 (0.003)	0.012 (0.005)	0.011 (0.003)	0.011 (0.002)
			40%	0.010 (0.004)	0.009 (0.003)	0.008 (0.002)	0.008 (0.004)	0.006 (0.002)	0.006 (0.001)
0.6	0.16	15	0%	211.000 (107.000)	245.000 (106.000)	394.000 (165.000)	54.300 (27.300)	39.500 (17.200)	53.600 (22.400)
			20%	56.700 (29.100)	112.000 (48.300)	121.000 (50.600)	75.900 (38.500)	66.600 (29.200)	75.600 (32.100)
			40%	0.029 (0.025)	0.019 (0.013)	0.017 (0.009)	0.030 (0.023)	0.020 (0.014)	0.015 (0.009)
		30	0%	49.400 (23.400)	0.006 (0.005)	42.400 (18.300)	21.500 (10.100)	0.006 (0.005)	13.100 (5.660)
			20%	110.000 (53.400)	41.400 (18.800)	126.000 (55.300)	45.400 (21.800)	7.720 (3.510)	49.100 (21.200)
			40%	0.015 (0.011)	0.013 (0.006)	0.012 (0.005)	0.015 (0.012)	0.011 (0.006)	0.010 (0.005)
		60	0%	0.004 (0.004)	0.003 (0.003)	0.002 (0.002)	0.004 (0.004)	0.003 (0.003)	0.002 (0.002)
			20%	7.180 (3.990)	9.610 (4.700)	6.320 (2.870)	0.009 (0.005)	0.008 (0.004)	2.490 (1.100)
			40%	0.014 (0.007)	0.012 (0.004)	0.012 (0.003)	0.011 (0.006)	0.010 (0.004)	0.009 (0.003)
		120	0%	0.003 (0.002)	0.002 (0.001)	0.001 (0.001)	0.003 (0.002)	0.002 (0.001)	0.001 (0.001)
			20%	0.014 (0.005)	9.290 (5.560)	1.230 (0.591)	0.008 (0.004)	1.340 (0.732)	0.007 (0.001)
			40%	0.014 (0.005)	0.013 (0.003)	0.012 (0.002)	0.008 (0.004)	0.009 (0.003)	0.009 (0.002)
	0.64	15	0%	0.022 (0.019)	0.015 (0.012)	0.009 (0.007)	0.022 (0.019)	0.015 (0.012)	0.009 (0.006)
			20%	0.032 (0.023)	0.024 (0.015)	0.020 (0.009)	0.029 (0.023)	0.021 (0.014)	0.015 (0.009)
			40%	0.026 (0.021)	0.019 (0.013)	0.015 (0.008)	0.029 (0.022)	0.022 (0.014)	0.015 (0.008)
		30	0%	0.008 (0.008)	0.005 (0.004)	0.004 (0.003)	0.008 (0.008)	0.005 (0.004)	0.004 (0.003)
			20%	0.019 (0.013)	0.017 (0.008)	0.016 (0.005)	0.015 (0.011)	0.012 (0.007)	0.011 (0.005)
			40%	0.018 (0.012)	0.014 (0.007)	0.012 (0.005)	0.017 (0.012)	0.013 (0.007)	0.012 (0.005)
		60	0%	0.004 (0.004)	0.003 (0.002)	0.002 (0.002)	0.004 (0.004)	0.003 (0.002)	0.002 (0.002)
			20%	0.017 (0.008)	0.016 (0.005)	0.015 (0.003)	0.012 (0.006)	0.010 (0.004)	0.010 (0.003)
			40%	0.016 (0.008)	0.014 (0.005)	0.012 (0.003)	0.014 (0.007)	0.012 (0.005)	0.011 (0.003)
		120	0%	0.002 (0.002)	0.002 (0.001)	0.001 (0.001)	0.002 (0.002)	0.002 (0.001)	0.001 (0.001)
			20%	0.016 (0.006)	0.015 (0.004)	0.014 (0.002)	0.010 (0.004)	0.009 (0.003)	0.009 (0.002)
			40%	0.016 (0.006)	0.015 (0.004)	0.014 (0.002)	0.013 (0.005)	0.012 (0.003)	0.012 (0.002)

Note: Population value for this parameter is 0. FE = Fixed Effect of Between-Time Random Slope; RE = Random Effect of Between-Time Random Slope; N = Sample Size; T = Measurement Occasions; PMD = Planned-Missing Data Percentage; ω = Reliability. The values outside the brackets represent the average point-estimate of the parameter across the successful replications. The values enclosed in the brackets represent the average standard deviation of the posterior distribution of the parameter across the successful replications.

Table 5.35: Rejection of the Random Effect of Random Slope α at Between-Individual Level

FE	RE	T	PMD	$\omega = 0.60$			$\omega = 0.80$			
				50	N 100	200	50	N 100	200	
0.3	0.16	15	0%	0.000	0.000	0.000	$\sigma_{\alpha_i}^2$	0.000	0.000	0.000
			20%	0.000	0.000	0.000		0.000	0.000	0.000
			40%	0.000	0.000	0.000		0.000	0.000	0.000
		30	0%	0.000	0.000	0.000		0.000	0.000	0.000
			20%	0.000	0.000	0.000		0.000	0.000	0.000
			40%	0.000	0.000	0.000		0.000	0.000	0.000
		60	0%	0.000	0.000	0.000		0.000	0.000	0.000
			20%	0.000	0.000	0.000		0.000	0.000	0.000
			40%	0.000	0.000	0.000		0.000	0.000	0.000
		120	0%	0.000	0.000	0.000		0.000	0.000	0.000
			20%	0.000	0.000	0.000		0.000	0.000	0.000
			40%	0.000	0.000	0.000		0.000	0.000	0.000
	0.64	15	0%	0.000	0.000	0.000		0.000	0.000	0.000
			20%	0.002	0.004	0.007		0.000	0.000	0.002
			40%	0.002	0.003	0.000		0.000	0.000	0.000
		30	0%	0.000	0.000	0.000		0.000	0.000	0.000
			20%	0.004	0.012	0.011		0.000	0.000	0.000
			40%	0.002	0.002	0.000		0.000	0.000	0.000
		60	0%	0.000	0.000	0.000		0.000	0.000	0.000
			20%	0.012	0.006	0.008		0.000	0.000	0.000
			40%	0.000	0.000	0.000		0.000	0.000	0.000
		120	0%	0.000	0.000	0.000		0.000	0.000	0.000
			20%	0.006	0.008	0.008		0.000	0.000	0.000
			40%	0.000	0.000	0.000		0.000	0.000	0.000
0.6	0.16	15	0%	0.000	0.000	0.000	0.000	0.000	0.000	
			20%	0.018	0.002	0.013	0.000	0.000	0.000	
			40%	0.000	0.025	0.052	0.000	0.000	0.000	
		30	0%	0.000	0.000	0.000	0.000	0.000	0.000	
			20%	0.008	0.015	0.023	0.000	0.000	0.000	
			40%	0.025	0.027	0.016	0.000	0.000	0.000	
		60	0%	0.000	0.000	0.000	0.000	0.000	0.000	
			20%	0.023	0.008	0.017	0.000	0.000	0.000	
			40%	0.025	0.029	0.009	0.000	0.000	0.000	
		120	0%	0.000	0.000	0.000	0.000	0.000	0.000	
			20%	0.023	0.025	0.023	0.000	0.000	0.000	
			40%	0.000	0.005	0.000	0.000	0.000	0.000	
	0.64	15	0%	0.000	0.000	0.000	0.000	0.000	0.000	
			20%	0.071	0.086	0.125	0.014	0.013	0.014	
			40%	0.000	0.000	0.011	0.000	0.000	0.000	
		30	0%	0.000	0.000	0.000	0.000	0.000	0.000	
			20%	0.126	0.151	0.208	0.007	0.012	0.020	
			40%	0.000	0.003	0.003	0.000	0.000	0.000	
		60	0%	0.000	0.000	0.000	0.000	0.000	0.000	
			20%	0.177	0.224	0.265	0.023	0.008	0.028	
			40%	0.003	0.012	0.008	0.000	0.000	0.000	
		120	0%	0.000	0.000	0.000	0.000	0.000	0.000	
			20%	0.210	0.284	0.381	0.014	0.008	0.033	
			40%	0.000	0.003	0.004	0.000	0.000	0.000	

Note: Population value for this parameter is 0. FE = Fixed Effect of Between-Time Random Slope; RE = Random Effect of Between-Time Random Slope; N = Sample Size; T = Measurement Occasions; PMD = Planned-Missing Data Percentage; ω = Reliability. The values represent the rejection averaged across successful replications. Values that were larger than the acceptable upper boundary of rejection (i.e., 0.20) were in bold.

Table 5.36: Rejection of the Random Effect of Random Slope β at Between-Individual Level

FE	RE	T	PMD	$\omega = 0.60$			$\omega = 0.80$			
				50	100	200	50	100	200	
0.3	0.16	15	0%	0.000	0.000	0.000	0.000	0.000	0.000	
			20%	0.000	0.000	0.000	0.000	0.000	0.000	
			40%	0.000	0.000	0.000	0.000	0.000	0.000	
		30	0%	0.000	0.000	0.000	0.000	0.000	0.000	
			20%	0.000	0.000	0.000	0.000	0.000	0.000	
			40%	0.000	0.000	0.000	0.000	0.000	0.000	
		60	0%	0.000	0.000	0.000	0.000	0.000	0.000	
			20%	0.000	0.000	0.000	0.000	0.000	0.000	
			40%	0.000	0.000	0.000	0.000	0.000	0.000	
		120	0%	0.000	0.000	0.000	0.000	0.000	0.000	
			20%	0.000	0.000	0.000	0.000	0.000	0.000	
			40%	0.000	0.000	0.000	0.000	0.000	0.000	
	0.64	15	0%	0.000	0.000	0.000	0.000	0.000	0.000	
			20%	0.000	0.000	0.000	0.000	0.000	0.000	
			40%	0.000	0.000	0.006	0.000	0.000	0.000	
		30	0%	0.000	0.000	0.000	0.000	0.000	0.000	
			20%	0.000	0.000	0.000	0.000	0.000	0.000	
			40%	0.000	0.000	0.003	0.000	0.000	0.000	
		60	0%	0.000	0.000	0.000	0.000	0.000	0.000	
			20%	0.000	0.000	0.000	0.000	0.000	0.000	
			40%	0.000	0.000	0.000	0.000	0.000	0.000	
		120	0%	0.000	0.000	0.000	0.000	0.000	0.000	
			20%	0.000	0.000	0.000	0.000	0.000	0.000	
			40%	0.000	0.000	0.000	0.000	0.000	0.000	
	0.6	0.16	15	0%	0.111	0.076	0.360	0.021	0.030	0.181
				20%	0.000	0.000	0.000	0.000	0.002	0.021
				40%	0.394	0.249	0.732	0.061	0.073	0.317
			30	0%	0.298	0.539	0.528	0.154	0.420	0.377
				20%	0.000	0.015	0.005	0.003	0.078	0.033
				40%	0.926	0.914	0.925	0.507	0.653	0.673
			60	0%	0.073	0.654	0.392	0.029	0.512	0.275
				20%	0.000	0.000	0.002	0.000	0.037	0.009
				40%	0.775	0.973	0.921	0.196	0.803	0.625
			120	0%	0.000	0.352	0.452	0.000	0.268	0.363
				20%	0.000	0.000	0.000	0.000	0.002	0.002
				40%	1.000	0.993	0.993	0.375	0.807	0.879
0.64		15	0%	0.018	0.014	0.084	0.010	0.012	0.064	
			20%	0.002	0.000	0.005	0.002	0.002	0.014	
			40%	0.058	0.054	0.288	0.030	0.020	0.109	
		30	0%	0.007	0.055	0.040	0.000	0.046	0.033	
			20%	0.000	0.000	0.000	0.000	0.015	0.002	
			40%	0.070	0.274	0.267	0.013	0.101	0.069	
		60	0%	0.000	0.010	0.002	0.000	0.010	0.002	
			20%	0.000	0.000	0.000	0.000	0.000	0.000	
			40%	0.013	0.188	0.154	0.000	0.051	0.009	
		120	0%	0.000	0.000	0.000	0.000	0.000	0.000	
			20%	0.000	0.000	0.000	0.000	0.000	0.000	
			40%	0.000	0.032	0.069	0.000	0.002	0.005	

Note: Population value for this parameter is 0. *FE* = Fixed Effect of Between-Time Random Slope; *RE* = Random Effect of Between-Time Random Slope; *N* = Sample Size; *T* = Measurement Occasions; *PMD* = Planned-Missing Data Percentage; ω = Reliability. The values represent the rejection averaged across successful replications. Values that were larger than the acceptable upper boundary of rejection (i.e., 0.20) were in bold.

Table 5.37: Rejection of the Random Effect of Random Slope τ at Between-Individual Level

FE	RE	T	PMD	$\omega = 0.60$			$\sigma_{\xi\tau_i}^2$	$\omega = 0.80$		
				50	N 100	200		50	N 100	200
0.3	0.16	15	0%	0.000	0.000	0.000	0.000	0.000	0.000	0.000
			20%	0.002	0.000	0.000		0.000	0.000	0.000
			40%	0.000	0.000	0.000		0.000	0.000	0.000
		30	0%	0.000	0.000	0.000		0.000	0.000	0.000
			20%	0.000	0.000	0.000		0.000	0.000	0.000
			40%	0.000	0.000	0.000		0.000	0.000	0.000
		60	0%	0.000	0.000	0.000		0.000	0.000	0.000
			20%	0.000	0.000	0.000		0.000	0.000	0.000
			40%	0.000	0.000	0.000		0.000	0.000	0.000
		120	0%	0.000	0.000	0.000		0.000	0.000	0.000
			20%	0.000	0.000	0.000		0.000	0.000	0.000
			40%	0.000	0.000	0.000		0.000	0.000	0.000
	0.64	15	0%	0.000	0.000	0.000		0.000	0.000	0.000
			20%	0.004	0.004	0.005		0.000	0.000	0.000
			40%	0.000	0.000	0.000		0.000	0.000	0.000
		30	0%	0.000	0.000	0.000		0.000	0.000	0.000
			20%	0.000	0.000	0.000		0.000	0.000	0.000
			40%	0.000	0.000	0.000		0.000	0.000	0.000
		60	0%	0.000	0.000	0.000		0.000	0.000	0.000
			20%	0.000	0.000	0.000		0.000	0.000	0.000
			40%	0.000	0.000	0.000		0.000	0.000	0.000
		120	0%	0.000	0.000	0.000		0.000	0.000	0.000
			20%	0.000	0.000	0.000		0.000	0.000	0.000
			40%	0.000	0.000	0.000		0.000	0.000	0.000
0.6	0.16	15	0%	0.013	0.009	0.016	0.003	0.002	0.003	
			20%	0.007	0.009	0.009	0.007	0.004	0.005	
			40%	0.000	0.000	0.000	0.000	0.000	0.000	
		30	0%	0.010	0.000	0.008	0.004	0.000	0.003	
			20%	0.061	0.015	0.045	0.013	0.002	0.012	
			40%	0.000	0.000	0.000	0.000	0.000	0.000	
		60	0%	0.000	0.000	0.000	0.000	0.000	0.000	
			20%	0.023	0.021	0.009	0.000	0.000	0.002	
			40%	0.000	0.000	0.000	0.000	0.000	0.000	
		120	0%	0.000	0.000	0.000	0.000	0.000	0.000	
			20%	0.000	0.111	0.006	0.000	0.006	0.000	
			40%	0.000	0.000	0.000	0.000	0.000	0.000	
	0.64	15	0%	0.000	0.000	0.000	0.000	0.000	0.000	
			20%	0.002	0.000	0.000	0.000	0.000	0.000	
			40%	0.000	0.000	0.004	0.003	0.000	0.000	
		30	0%	0.000	0.000	0.000	0.000	0.000	0.000	
			20%	0.000	0.000	0.000	0.000	0.000	0.000	
			40%	0.003	0.000	0.000	0.000	0.000	0.000	
		60	0%	0.000	0.000	0.000	0.000	0.000	0.000	
			20%	0.000	0.000	0.000	0.000	0.000	0.000	
			40%	0.000	0.000	0.000	0.000	0.000	0.000	
		120	0%	0.000	0.000	0.000	0.000	0.000	0.000	
			20%	0.000	0.000	0.000	0.000	0.000	0.000	
			40%	0.000	0.000	0.000	0.000	0.000	0.000	

Note: Population value for this parameter is 0. FE = Fixed Effect of Between-Time Random Slope; RE = Random Effect of Between-Time Random Slope; N = Sample Size; T = Measurement Occasions; PMD = Planned-Missing Data Percentage; ω = Reliability. The values represent the rejection averaged across successful replications. Values that were larger than the acceptable upper boundary of rejection (i.e., 0.20) were in bold.

5.4.5 Random Intercept at Between-Individual Level

Fixed Effect ($\gamma_{X_i}, \gamma_{M_i}, \gamma_{Y_i}$)

The fixed effect (mean) of the random intercepts at the between-individual level was simulated with a population value of 0. An inspect of the average point-estimate of the parameters and the corresponding average standard deviation of the posterior distributions over successful replications (see Table 5.38, Table 5.39, and Table 5.40) showed that both the point-estimates and the standard deviation of the posterior distributions were small and close to 0.

Power As evident in Table 5.41, Table 5.42, and Table 5.43, the rejection for the parameters were all 0.00 for all combinations of the simulation conditions. This indicated that all the 90% HDIs for each of the respective parameter contained the ROPE, implying that the hypotheses that the parameter was 0 were correctly accepted for all conditions.

Random Effect ($\sigma_{\xi_{X_i}}^2, \sigma_{\xi_{M_i}}^2, \sigma_{\xi_{Y_i}}^2$)

Table 5.44, Table 5.45, and Table 5.46 contained the average point-estimate and the average standard posterior of the posterior distribution of the between-individual random intercept of X, M, and Y variables. It was clear from the table that all of the parameters were over-estimated to a certain extend depending on the experimental conditions. It was also noted that the standard deviation of the posterior distribution decreased substantially with the increase of N .

Relative Bias The relative bias for all three parameters of interest had exceeded the acceptable range of bias as evident in Table 5.50, Table 5.51, and Table 5.52. Reliability ω seemed to have played a notable role on the magnitude of bias, with a higher reliability ($\omega = 0.80$) related to a smaller degree of relative bias as compared to lower reliability ($\omega = 0.60$). A larger sample size (N) was also related to a smaller magnitude of relative bias compared to smaller sample size. A higher degree of *PMD* was

also related to higher relative bias. The variance of the between-time random slope also seemed to have an effect on the relative bias of the variance of the between-individual random intercept ($RE = 0.16$ conditions tended to have smaller relative bias than the $RE = 0.64$ conditions).

Coverage The coverage of all three parameters were also lower than the acceptable rate and close to 0 (i.e., none of the 90% HDI of the respective parameter contained the true value across the replications). This was likely due to the extreme over-estimation of the parameters. See Table 5.50, Table 5.51, and Table 5.52.

Rejection The rejection for the three parameters in all conditions were 1.00 (i.e. all of the 90% HDI of the respective parameter did not contain the ROPE across the replications, correctly suggesting the parameter was not 0, albeit the large relative bias). The values were presented in Table 5.53, Table 5.54, and Table 5.55.

Table 5.38: Descriptive Statistics for Fixed Effect of Random Intercept of X at Between-Individual Level

FE	RE	T	PMD	$\omega = 0.60$			$\omega = 0.80$		
				50	100	200	50	100	200
0.3	0.16	15	0%	0.019 (0.255)	0.006 (0.182)	-0.003 (0.127)	0.002 (0.179)	0.002 (0.126)	0.002 (0.090)
			20%	-0.009 (0.262)	0.017 (0.185)	-0.001 (0.131)	0.006 (0.183)	0.005 (0.130)	-0.002 (0.091)
			40%	0.000 (0.269)	0.013 (0.192)	-0.001 (0.135)	0.005 (0.188)	0.011 (0.133)	-0.007 (0.094)
			0%	0.010 (0.264)	0.002 (0.179)	-0.008 (0.126)	0.008 (0.186)	0.002 (0.124)	-0.004 (0.087)
		30	20%	0.029 (0.271)	0.005 (0.182)	-0.007 (0.128)	0.016 (0.187)	0.002 (0.125)	-0.006 (0.088)
			40%	-0.001 (0.280)	-0.001 (0.188)	-0.014 (0.132)	0.015 (0.194)	0.004 (0.129)	-0.004 (0.091)
			0%	-0.021 (0.262)	0.001 (0.183)	0.000 (0.126)	-0.013 (0.182)	0.005 (0.125)	-0.009 (0.088)
			20%	-0.011 (0.269)	0.001 (0.185)	0.003 (0.129)	-0.015 (0.185)	-0.004 (0.128)	-0.004 (0.089)
		60	40%	-0.013 (0.275)	-0.011 (0.191)	-0.026 (0.133)	-0.010 (0.190)	-0.006 (0.130)	0.002 (0.092)
			0%	0.011 (0.262)	-0.007 (0.181)	0.001 (0.129)	0.021 (0.182)	0.009 (0.125)	0.003 (0.089)
			20%	0.012 (0.269)	0.002 (0.185)	0.003 (0.131)	0.005 (0.184)	0.001 (0.126)	0.006 (0.090)
			40%	0.005 (0.280)	0.022 (0.191)	0.002 (0.136)	0.010 (0.190)	-0.003 (0.131)	-0.006 (0.093)
	0.64	15	0%	-0.013 (0.323)	-0.007 (0.227)	-0.019 (0.159)	-0.001 (0.215)	0.003 (0.151)	0.007 (0.106)
			20%	0.015 (0.330)	-0.028 (0.231)	-0.018 (0.162)	0.002 (0.220)	-0.004 (0.153)	-0.002 (0.108)
			40%	0.017 (0.337)	0.009 (0.237)	0.001 (0.167)	0.001 (0.225)	-0.011 (0.158)	-0.003 (0.112)
			0%	0.011 (0.336)	-0.015 (0.223)	-0.011 (0.158)	0.006 (0.224)	0.006 (0.149)	-0.008 (0.106)
		30	20%	-0.004 (0.342)	0.011 (0.227)	0.004 (0.162)	-0.002 (0.228)	-0.002 (0.151)	-0.001 (0.107)
			40%	-0.014 (0.352)	0.008 (0.234)	-0.011 (0.167)	0.008 (0.234)	0.008 (0.155)	-0.005 (0.110)
			0%	-0.016 (0.330)	-0.001 (0.225)	-0.012 (0.162)	-0.014 (0.219)	-0.001 (0.150)	-0.003 (0.107)
			20%	-0.029 (0.338)	0.004 (0.229)	-0.003 (0.165)	-0.001 (0.220)	0.007 (0.152)	0.001 (0.108)
		60	40%	-0.002 (0.347)	-0.004 (0.234)	0.007 (0.170)	-0.019 (0.227)	-0.008 (0.157)	-0.014 (0.112)
			0%	0.010 (0.329)	0.000 (0.228)	-0.004 (0.160)	0.029 (0.217)	-0.008 (0.151)	0.005 (0.106)
			20%	0.030 (0.332)	0.000 (0.232)	0.005 (0.163)	0.032 (0.221)	-0.005 (0.154)	-0.006 (0.108)
			40%	0.020 (0.342)	-0.005 (0.237)	0.000 (0.166)	0.028 (0.227)	0.005 (0.158)	-0.005 (0.111)
0.6	0.16	15	0%	0.022 (0.294)	-0.012 (0.210)	0.004 (0.148)	0.011 (0.198)	0.005 (0.140)	0.001 (0.099)
		20%	-0.008 (0.309)	0.024 (0.217)	0.005 (0.153)	-0.010 (0.206)	-0.003 (0.145)	0.003 (0.102)	
		40%	-0.007 (0.317)	0.003 (0.219)	-0.008 (0.158)	0.011 (0.211)	0.017 (0.150)	0.009 (0.104)	
		0%	0.003 (0.313)	0.005 (0.209)	-0.005 (0.148)	0.028 (0.205)	0.002 (0.139)	0.005 (0.100)	
	30	20%	0.037 (0.319)	-0.017 (0.212)	-0.001 (0.151)	0.018 (0.210)	0.003 (0.142)	-0.012 (0.101)	
		40%	0.013 (0.334)	0.010 (0.220)	0.008 (0.156)	0.009 (0.223)	-0.005 (0.146)	-0.010 (0.104)	
		0%	0.010 (0.309)	-0.011 (0.214)	0.003 (0.150)	-0.004 (0.205)	-0.006 (0.143)	0.000 (0.101)	
		20%	-0.011 (0.314)	0.012 (0.218)	-0.001 (0.154)	-0.015 (0.207)	0.006 (0.145)	-0.003 (0.102)	
	60	40%	-0.010 (0.330)	0.000 (0.226)	-0.009 (0.160)	0.015 (0.213)	-0.010 (0.151)	0.000 (0.105)	
		0%	0.002 (0.304)	0.003 (0.214)	-0.006 (0.153)	-0.009 (0.202)	-0.006 (0.143)	-0.009 (0.101)	
		20%	0.015 (0.321)	-0.017 (0.216)	-0.003 (0.152)	0.008 (0.214)	0.005 (0.144)	-0.005 (0.103)	
		40%	-0.039 (0.344)	-0.010 (0.228)	-0.027 (0.157)	-0.047 (0.220)	0.001 (0.151)	-0.007 (0.107)	
0.64	15	0%	-0.023 (0.354)	-0.008 (0.257)	-0.020 (0.182)	0.009 (0.232)	0.011 (0.170)	-0.009 (0.119)	
		20%	0.013 (0.365)	0.006 (0.264)	0.008 (0.189)	-0.013 (0.241)	-0.001 (0.173)	0.010 (0.123)	
		40%	0.015 (0.371)	-0.014 (0.262)	-0.006 (0.190)	0.020 (0.244)	0.000 (0.176)	-0.003 (0.124)	
		0%	0.056 (0.381)	0.008 (0.256)	0.008 (0.181)	0.000 (0.249)	-0.001 (0.166)	-0.002 (0.118)	
	30	20%	0.025 (0.391)	0.008 (0.259)	-0.007 (0.184)	0.019 (0.253)	0.022 (0.169)	-0.008 (0.120)	
		40%	0.040 (0.388)	0.007 (0.270)	-0.003 (0.188)	0.038 (0.258)	-0.001 (0.171)	-0.003 (0.121)	
		0%	-0.007 (0.374)	0.004 (0.258)	0.006 (0.182)	-0.017 (0.247)	0.002 (0.169)	0.001 (0.118)	
		20%	-0.004 (0.386)	0.000 (0.265)	-0.007 (0.184)	-0.004 (0.249)	0.001 (0.171)	-0.008 (0.120)	
	60	40%	-0.015 (0.386)	0.016 (0.269)	-0.018 (0.191)	-0.037 (0.254)	0.015 (0.174)	0.005 (0.120)	
		0%	0.018 (0.380)	0.007 (0.261)	-0.016 (0.188)	0.002 (0.247)	0.000 (0.170)	-0.010 (0.122)	
		20%	0.039 (0.387)	-0.019 (0.267)	-0.005 (0.192)	0.013 (0.250)	-0.003 (0.172)	0.002 (0.124)	
		40%	0.042 (0.368)	0.000 (0.262)	0.001 (0.191)	0.008 (0.253)	-0.004 (0.175)	-0.002 (0.126)	

Note: Population value for this parameter is 0. FE = Fixed Effect of Between-Time Random Slope; RE = Random Effect of Between-Time Random Slope; N = Sample Size; T = Measurement Occasions; PMD = Planned-Missing Data Percentage; ω = Reliability. The values outside the brackets represent the average point-estimate of the parameter across the successful replications. The values enclosed in the brackets represent the average standard deviation of the posterior distribution of the parameter across the successful replications.

Table 5.39: Descriptive Statistics for Fixed Effect of Random Intercept of M at Between-Individual Level

FE	RE	T	PMD	$\omega = 0.60$			$\omega = 0.80$			
				50	100	200	50	100	200	
0.3	0.16	15	0%	0.002 (0.259)	-0.003 (0.182)	-0.006 (0.127)	γ_{M_i}	-0.012 (0.182)	-0.005 (0.128)	0.003 (0.089)
			20%	-0.024 (0.266)	0.007 (0.188)	-0.002 (0.132)	-0.010 (0.187)	0.001 (0.132)	-0.003 (0.091)	
			40%	-0.034 (0.273)	0.006 (0.192)	0.004 (0.135)	-0.020 (0.191)	0.008 (0.133)	-0.004 (0.093)	
		30	0%	-0.001 (0.254)	0.003 (0.187)	0.002 (0.131)	-0.007 (0.179)	-0.003 (0.130)	0.005 (0.091)	
			20%	0.015 (0.264)	-0.003 (0.192)	0.005 (0.133)	0.006 (0.181)	-0.003 (0.132)	0.004 (0.093)	
			40%	-0.013 (0.270)	-0.008 (0.198)	-0.003 (0.138)	0.005 (0.186)	0.005 (0.135)	0.004 (0.095)	
		60	0%	-0.003 (0.262)	-0.005 (0.181)	0.005 (0.125)	-0.003 (0.182)	-0.002 (0.124)	-0.003 (0.087)	
			20%	0.005 (0.268)	-0.009 (0.183)	0.008 (0.128)	0.000 (0.184)	-0.009 (0.126)	-0.001 (0.088)	
			40%	0.007 (0.275)	-0.011 (0.188)	-0.014 (0.132)	0.004 (0.188)	-0.013 (0.130)	0.006 (0.091)	
		120	0%	-0.014 (0.250)	-0.001 (0.177)	0.003 (0.126)	-0.004 (0.174)	0.007 (0.122)	0.004 (0.087)	
			20%	-0.032 (0.257)	0.001 (0.183)	0.006 (0.128)	-0.013 (0.176)	0.003 (0.124)	0.008 (0.088)	
			40%	-0.025 (0.267)	0.017 (0.188)	0.002 (0.133)	-0.013 (0.181)	0.005 (0.128)	-0.001 (0.091)	
	0.64	15	0%	-0.038 (0.327)	0.008 (0.225)	-0.016 (0.161)	-0.021 (0.219)	0.008 (0.151)	0.009 (0.107)	
			20%	-0.001 (0.337)	-0.021 (0.232)	-0.018 (0.167)	-0.009 (0.223)	0.009 (0.155)	0.003 (0.111)	
			40%	-0.022 (0.340)	0.020 (0.236)	0.004 (0.171)	-0.033 (0.229)	-0.004 (0.160)	0.005 (0.114)	
		30	0%	-0.008 (0.325)	-0.025 (0.231)	-0.012 (0.162)	-0.007 (0.216)	-0.009 (0.155)	-0.004 (0.109)	
			20%	-0.028 (0.334)	0.008 (0.238)	0.007 (0.167)	-0.015 (0.221)	-0.009 (0.158)	0.000 (0.111)	
			40%	-0.027 (0.342)	-0.011 (0.244)	-0.006 (0.174)	-0.003 (0.227)	-0.001 (0.161)	-0.002 (0.113)	
		60	0%	-0.006 (0.330)	-0.021 (0.222)	-0.007 (0.158)	-0.006 (0.220)	-0.011 (0.148)	-0.003 (0.105)	
			20%	-0.022 (0.336)	-0.010 (0.226)	0.000 (0.161)	0.010 (0.221)	-0.006 (0.150)	-0.003 (0.107)	
			40%	0.005 (0.347)	-0.020 (0.234)	0.008 (0.167)	-0.013 (0.226)	-0.015 (0.155)	-0.010 (0.110)	
		120	0%	-0.031 (0.313)	0.001 (0.222)	0.007 (0.156)	-0.007 (0.209)	-0.004 (0.148)	0.010 (0.104)	
			20%	-0.006 (0.318)	0.006 (0.227)	0.012 (0.159)	0.003 (0.210)	-0.004 (0.150)	-0.003 (0.105)	
			40%	-0.021 (0.332)	-0.014 (0.230)	0.013 (0.163)	0.001 (0.217)	0.004 (0.154)	-0.002 (0.109)	
0.6	0.16	15	0%	-0.016 (0.296)	-0.014 (0.208)	0.010 (0.148)	-0.014 (0.198)	0.001 (0.141)	-0.001 (0.099)	
			20%	-0.029 (0.310)	0.017 (0.218)	-0.003 (0.153)	-0.032 (0.208)	-0.006 (0.146)	0.001 (0.101)	
			40%	-0.027 (0.322)	-0.005 (0.216)	0.013 (0.156)	-0.026 (0.211)	0.004 (0.148)	0.010 (0.104)	
	30	0%	-0.018 (0.299)	0.004 (0.218)	0.003 (0.155)	0.007 (0.199)	-0.003 (0.144)	0.009 (0.104)		
		20%	0.015 (0.310)	-0.018 (0.224)	0.003 (0.160)	0.000 (0.202)	0.005 (0.150)	-0.007 (0.106)		
		40%	-0.008 (0.320)	0.018 (0.230)	0.003 (0.164)	0.007 (0.213)	-0.005 (0.152)	-0.005 (0.109)		
	60	0%	0.002 (0.308)	-0.014 (0.212)	0.007 (0.149)	0.002 (0.204)	-0.013 (0.142)	0.000 (0.100)		
		20%	-0.008 (0.317)	0.004 (0.216)	-0.002 (0.153)	-0.010 (0.209)	-0.005 (0.145)	0.000 (0.102)		
		40%	-0.018 (0.335)	-0.023 (0.225)	-0.005 (0.159)	0.004 (0.217)	-0.016 (0.150)	0.000 (0.104)		
	120	0%	-0.024 (0.288)	-0.003 (0.210)	0.006 (0.149)	0.005 (0.194)	-0.010 (0.141)	0.000 (0.099)		
		20%	-0.016 (0.306)	-0.018 (0.211)	0.005 (0.150)	-0.013 (0.205)	-0.003 (0.143)	0.006 (0.100)		
		40%	0.041 (0.365)	-0.006 (0.224)	-0.014 (0.154)	-0.022 (0.198)	0.001 (0.148)	0.002 (0.105)		
0.64	15	0%	-0.046 (0.355)	-0.002 (0.254)	-0.015 (0.184)	-0.011 (0.232)	0.009 (0.168)	-0.011 (0.120)		
		20%	-0.024 (0.370)	0.008 (0.264)	0.002 (0.192)	-0.025 (0.243)	0.008 (0.173)	0.006 (0.125)		
		40%	-0.010 (0.368)	-0.004 (0.261)	0.006 (0.193)	0.001 (0.247)	0.004 (0.175)	-0.003 (0.126)		
	30	0%	0.033 (0.360)	0.014 (0.265)	0.012 (0.188)	-0.011 (0.237)	-0.010 (0.173)	0.006 (0.123)		
		20%	-0.006 (0.371)	-0.002 (0.272)	0.011 (0.192)	0.004 (0.241)	0.014 (0.177)	-0.004 (0.125)		
		40%	0.015 (0.366)	-0.003 (0.282)	0.005 (0.199)	0.017 (0.245)	-0.006 (0.178)	0.010 (0.129)		
	60	0%	-0.010 (0.372)	-0.005 (0.252)	0.011 (0.182)	-0.003 (0.247)	-0.003 (0.165)	0.003 (0.118)		
		20%	-0.003 (0.383)	-0.022 (0.259)	0.001 (0.186)	-0.009 (0.250)	-0.010 (0.167)	0.000 (0.121)		
		40%	-0.010 (0.383)	0.018 (0.267)	-0.002 (0.197)	-0.010 (0.255)	-0.001 (0.171)	0.005 (0.123)		
	120	0%	-0.013 (0.365)	0.009 (0.256)	-0.005 (0.185)	0.018 (0.237)	0.007 (0.166)	-0.004 (0.120)		
		20%	-0.006 (0.368)	-0.013 (0.260)	0.007 (0.188)	-0.016 (0.240)	0.003 (0.168)	0.010 (0.122)		
		40%	-0.013 (0.358)	0.010 (0.253)	0.024 (0.188)	-0.011 (0.246)	-0.004 (0.172)	0.005 (0.124)		

Note: Population value for this parameter is 0. FE = Fixed Effect of Between-Time Random Slope; RE = Random Effect of Between-Time Random Slope; N = Sample Size; T = Measurement Occasions; PMD = Planned-Missing Data Percentage; ω = Reliability. The values outside the brackets represent the average point-estimate of the parameter across the successful replications. The values enclosed in the brackets represent the average standard deviation of the posterior distribution of the parameter across the successful replications.

Table 5.40: Descriptive Statistics for Fixed Effect of Random Intercept of Y at Between-Individual Level

FE	RE	T	PMD	$\omega = 0.60$			$\omega = 0.80$		
				50	N 100	200	50	N 100	200
0.3	0.16	15	0%	0.007 (0.261)	-0.003 (0.184)	-0.001 (0.129)	-0.002 (0.185)	-0.005 (0.130)	0.000 (0.092)
			20%	-0.013 (0.269)	0.011 (0.189)	0.000 (0.133)	0.001 (0.190)	0.000 (0.134)	-0.001 (0.094)
			40%	-0.023 (0.277)	-0.001 (0.196)	0.005 (0.137)	-0.006 (0.195)	0.008 (0.137)	-0.002 (0.096)
			40%	-0.011 (0.256)	-0.001 (0.186)	0.002 (0.128)	-0.007 (0.178)	-0.009 (0.130)	0.005 (0.089)
		30	20%	0.021 (0.264)	-0.011 (0.189)	0.006 (0.131)	0.001 (0.181)	-0.010 (0.131)	0.002 (0.091)
			40%	-0.023 (0.274)	-0.020 (0.195)	-0.001 (0.136)	-0.005 (0.188)	-0.005 (0.135)	0.005 (0.093)
			40%	-0.021 (0.257)	0.006 (0.187)	0.009 (0.126)	-0.011 (0.179)	0.004 (0.128)	0.000 (0.088)
			40%	0.001 (0.266)	-0.002 (0.187)	0.006 (0.129)	-0.006 (0.182)	-0.005 (0.131)	0.005 (0.089)
		60	40%	-0.014 (0.272)	-0.008 (0.195)	-0.015 (0.134)	-0.013 (0.186)	-0.001 (0.134)	0.008 (0.092)
			40%	0.003 (0.256)	-0.002 (0.182)	0.003 (0.127)	0.012 (0.178)	0.007 (0.126)	0.003 (0.088)
			40%	0.003 (0.265)	0.000 (0.186)	0.000 (0.129)	0.002 (0.179)	0.002 (0.127)	0.004 (0.089)
			40%	-0.003 (0.275)	0.012 (0.192)	0.005 (0.134)	-0.003 (0.187)	0.000 (0.132)	-0.003 (0.091)
	0.64	15	0%	-0.025 (0.332)	0.003 (0.231)	-0.012 (0.162)	-0.015 (0.224)	0.002 (0.157)	0.009 (0.110)
			20%	0.001 (0.341)	-0.025 (0.238)	-0.008 (0.167)	0.007 (0.232)	-0.001 (0.160)	0.001 (0.113)
			40%	-0.004 (0.354)	0.015 (0.248)	0.001 (0.172)	-0.005 (0.238)	0.001 (0.166)	-0.002 (0.116)
			40%	0.010 (0.326)	-0.037 (0.232)	-0.003 (0.160)	0.010 (0.218)	-0.018 (0.156)	0.001 (0.108)
		30	20%	-0.005 (0.335)	-0.015 (0.238)	0.021 (0.164)	0.001 (0.222)	-0.023 (0.158)	0.012 (0.110)
			40%	-0.004 (0.345)	-0.017 (0.245)	-0.004 (0.170)	0.004 (0.230)	-0.015 (0.164)	0.007 (0.112)
			40%	-0.009 (0.327)	-0.007 (0.231)	-0.006 (0.162)	-0.009 (0.219)	0.000 (0.155)	0.003 (0.107)
			40%	-0.022 (0.334)	0.004 (0.237)	0.007 (0.164)	0.007 (0.220)	0.002 (0.157)	0.009 (0.109)
		60	40%	-0.004 (0.345)	-0.014 (0.243)	0.013 (0.171)	-0.017 (0.226)	-0.003 (0.162)	-0.006 (0.112)
			40%	0.010 (0.324)	0.002 (0.230)	0.010 (0.158)	-0.003 (0.214)	-0.009 (0.153)	0.009 (0.105)
			40%	0.006 (0.326)	0.005 (0.236)	0.015 (0.161)	0.009 (0.217)	-0.010 (0.155)	0.002 (0.106)
			40%	0.008 (0.341)	-0.029 (0.240)	0.013 (0.163)	0.007 (0.225)	0.008 (0.160)	0.000 (0.110)
0.6	0.16	15	0%	-0.003 (0.299)	-0.014 (0.217)	0.011 (0.151)	-0.003 (0.204)	0.000 (0.149)	0.000 (0.103)
			20%	-0.017 (0.318)	0.011 (0.224)	-0.003 (0.156)	-0.029 (0.217)	-0.004 (0.152)	0.003 (0.106)
			40%	-0.020 (0.329)	-0.002 (0.229)	-0.004 (0.160)	0.001 (0.219)	0.010 (0.158)	0.005 (0.108)
			40%	0.001 (0.304)	-0.004 (0.218)	0.009 (0.152)	0.012 (0.201)	-0.010 (0.146)	0.013 (0.103)
	30	20%	0.020 (0.306)	-0.031 (0.221)	0.001 (0.156)	0.010 (0.203)	-0.007 (0.150)	0.000 (0.105)	
		40%	0.006 (0.327)	0.003 (0.229)	0.014 (0.160)	-0.008 (0.216)	-0.012 (0.155)	0.003 (0.108)	
		40%	-0.005 (0.303)	0.000 (0.220)	0.010 (0.150)	-0.001 (0.202)	-0.008 (0.147)	0.001 (0.101)	
		40%	-0.014 (0.310)	0.020 (0.225)	0.006 (0.153)	-0.009 (0.207)	0.007 (0.151)	0.002 (0.103)	
	60	40%	-0.020 (0.328)	-0.006 (0.232)	0.014 (0.160)	0.003 (0.212)	-0.001 (0.155)	0.001 (0.105)	
		40%	0.000 (0.293)	0.008 (0.215)	0.003 (0.149)	-0.007 (0.202)	-0.002 (0.145)	-0.005 (0.099)	
		40%	-0.017 (0.314)	-0.008 (0.218)	0.000 (0.151)	-0.006 (0.210)	0.008 (0.146)	0.005 (0.101)	
		40%	0.188 (0.362)	0.003 (0.231)	-0.016 (0.155)	0.087 (0.204)	0.005 (0.153)	-0.003 (0.105)	
0.64	15	0%	-0.016 (0.369)	-0.001 (0.262)	-0.010 (0.182)	0.002 (0.246)	0.006 (0.176)	-0.014 (0.121)	
		20%	0.010 (0.384)	0.005 (0.271)	0.002 (0.189)	-0.010 (0.256)	0.002 (0.180)	0.001 (0.126)	
		40%	0.006 (0.387)	-0.002 (0.269)	-0.002 (0.194)	0.020 (0.263)	-0.005 (0.184)	-0.008 (0.128)	
		40%	0.029 (0.366)	-0.003 (0.265)	0.011 (0.187)	-0.006 (0.240)	-0.008 (0.174)	0.005 (0.123)	
	30	20%	0.005 (0.374)	-0.009 (0.271)	0.010 (0.190)	0.010 (0.245)	0.014 (0.178)	0.004 (0.125)	
		40%	0.009 (0.375)	0.002 (0.282)	0.009 (0.200)	0.015 (0.249)	-0.003 (0.183)	0.000 (0.130)	
		40%	-0.009 (0.373)	0.018 (0.264)	0.018 (0.183)	0.000 (0.244)	0.006 (0.174)	0.003 (0.119)	
		40%	-0.004 (0.381)	0.006 (0.273)	0.006 (0.187)	-0.002 (0.249)	0.010 (0.177)	0.003 (0.122)	
	60	40%	-0.024 (0.389)	0.024 (0.277)	0.016 (0.199)	-0.016 (0.253)	0.018 (0.181)	0.006 (0.123)	
		40%	0.000 (0.369)	0.021 (0.262)	-0.005 (0.185)	0.016 (0.237)	0.012 (0.170)	-0.001 (0.120)	
		40%	0.009 (0.375)	-0.015 (0.266)	0.000 (0.188)	-0.006 (0.243)	0.002 (0.173)	0.008 (0.123)	

Note: Population value for this parameter is 0. FE = Fixed Effect of Between-Time Random Slope; RE = Random Effect of Between-Time Random Slope; N = Sample Size; T = Measurement Occasions; PMD = Planned-Missing Data Percentage; ω = Reliability. The values outside the brackets represent the average point-estimate of the parameter across the successful replications. The values enclosed in the brackets represent the average standard deviation of the posterior distribution of the parameter across the successful replications.

Table 5.41: Rejection of the Fixed Effect of Random Intercept of X at Between-Individual Level

FE	RE	T	PMD	$\omega = 0.60$			γ_{X_i}	$\omega = 0.80$		
				50	100	200		50	100	200
0.3	0.16	15	0%	0.018	0.033	0.024		0.014	0.032	0.007
			20%	0.024	0.038	0.017		0.028	0.018	0.013
			40%	0.025	0.040	0.027		0.024	0.035	0.009
		30	0%	0.020	0.030	0.016		0.034	0.032	0.007
			20%	0.048	0.020	0.009		0.022	0.020	0.009
			40%	0.038	0.027	0.018		0.024	0.027	0.008
		60	0%	0.022	0.024	0.008		0.016	0.008	0.008
			20%	0.032	0.032	0.017		0.024	0.014	0.012
			40%	0.028	0.015	0.003		0.018	0.008	0.007
		120	0%	0.024	0.024	0.028		0.034	0.030	0.012
			20%	0.038	0.030	0.016		0.020	0.026	0.014
			40%	0.016	0.055	0.021		0.026	0.022	0.007
	0.64	15	0%	0.024	0.024	0.015		0.015	0.035	0.016
			20%	0.030	0.021	0.029		0.022	0.011	0.022
			40%	0.033	0.036	0.029		0.028	0.020	0.015
		30	0%	0.032	0.025	0.017		0.025	0.031	0.018
			20%	0.046	0.035	0.018		0.025	0.024	0.012
			40%	0.026	0.035	0.015		0.038	0.030	0.013
		60	0%	0.029	0.034	0.017		0.045	0.024	0.015
			20%	0.027	0.048	0.008		0.020	0.036	0.008
			40%	0.020	0.028	0.012		0.027	0.015	0.007
		120	0%	0.030	0.032	0.016		0.026	0.022	0.022
			20%	0.030	0.038	0.030		0.024	0.028	0.024
			40%	0.052	0.020	0.022		0.039	0.038	0.018
0.6	0.16	15	0%	0.053	0.028	0.029	0.017	0.036	0.016	
			20%	0.024	0.047	0.031	0.021	0.033	0.014	
			40%	0.030	0.032	0.024	0.011	0.044	0.022	
		30	0%	0.024	0.021	0.021	0.038	0.007	0.018	
			20%	0.046	0.017	0.027	0.026	0.023	0.016	
			40%	0.041	0.027	0.031	0.030	0.019	0.014	
		60	0%	0.032	0.023	0.025	0.011	0.032	0.005	
			20%	0.028	0.041	0.019	0.017	0.022	0.009	
			40%	0.029	0.040	0.012	0.047	0.019	0.012	
		120	0%	0.029	0.037	0.036	0.019	0.011	0.006	
			20%	0.033	0.020	0.043	0.014	0.026	0.018	
			40%	0.000	0.022	0.027	0.000	0.040	0.017	
	0.64	15	0%	0.030	0.026	0.022	0.034	0.026	0.018	
			20%	0.031	0.040	0.020	0.014	0.013	0.008	
			40%	0.029	0.025	0.038	0.028	0.033	0.007	
		30	0%	0.053	0.029	0.032	0.030	0.017	0.015	
			20%	0.041	0.041	0.040	0.037	0.044	0.015	
			40%	0.031	0.046	0.030	0.053	0.026	0.019	
		60	0%	0.029	0.044	0.013	0.019	0.039	0.011	
			20%	0.044	0.028	0.013	0.027	0.025	0.019	
			40%	0.018	0.026	0.021	0.025	0.030	0.012	
		120	0%	0.035	0.040	0.021	0.028	0.032	0.010	
			20%	0.021	0.040	0.025	0.039	0.030	0.023	
			40%	0.059	0.041	0.036	0.029	0.036	0.017	

Note: Population value for this parameter is 0. FE = Fixed Effect of Between-Time Random Slope; RE = Random Effect of Between-Time Random Slope; N = Sample Size; T = Measurement Occasions; PMD = Planned-Missing Data Percentage; ω = Reliability. The values represent the rejection averaged across successful replications. Values that were larger than the acceptable upper boundary of rejection (i.e., 0.20) were in bold.

Table 5.42: Rejection of the Fixed Effect of Random Intercept of M at Between-Individual Level

FE	RE	T	PMD	$\omega = 0.60$			$\omega = 0.80$				
				50	100	200	50	100	200		
0.3	0.16	15	0%	0.040	0.022	0.015	γ_{M_i}	0.030	0.024	0.011	
			20%	0.016	0.026	0.021		0.022	0.020	0.004	
			40%	0.037	0.025	0.039		0.028	0.045	0.021	
		30	0%	0.028	0.030	0.013		0.036	0.016	0.002	
			20%	0.042	0.018	0.018		0.030	0.026	0.007	
			40%	0.024	0.019	0.028		0.032	0.025	0.023	
		60	0%	0.028	0.042	0.023		0.028	0.016	0.012	
			20%	0.028	0.036	0.019		0.043	0.022	0.008	
			40%	0.020	0.040	0.015		0.026	0.026	0.021	
		120	0%	0.026	0.032	0.024		0.022	0.024	0.016	
			20%	0.026	0.020	0.030		0.018	0.028	0.026	
			40%	0.028	0.041	0.026		0.008	0.028	0.015	
	0.64	15	0%	0.031	0.042	0.021		0.024	0.022	0.024	
			20%	0.033	0.028	0.017		0.029	0.026	0.020	
			40%	0.040	0.049	0.042		0.024	0.023	0.009	
		30	0%	0.047	0.027	0.025		0.038	0.021	0.020	
			20%	0.038	0.033	0.016		0.025	0.018	0.014	
			40%	0.028	0.031	0.023		0.038	0.026	0.024	
		60	0%	0.033	0.026	0.019		0.037	0.034	0.017	
			20%	0.037	0.032	0.006		0.033	0.028	0.012	
			40%	0.031	0.042	0.024		0.034	0.019	0.007	
		120	0%	0.030	0.038	0.028		0.028	0.018	0.018	
			20%	0.030	0.046	0.046		0.020	0.024	0.024	
			40%	0.031	0.029	0.026		0.024	0.032	0.014	
	0.6	0.16	15	0%	0.040	0.018		0.032	0.028	0.017	0.016
				20%	0.035	0.039		0.020	0.019	0.033	0.021
				40%	0.045	0.038		0.049	0.004	0.033	0.016
			30	0%	0.014	0.030		0.019	0.038	0.022	0.018
				20%	0.053	0.028		0.023	0.039	0.025	0.014
				40%	0.037	0.043		0.034	0.030	0.033	0.011
			60	0%	0.017	0.028		0.022	0.035	0.020	0.018
				20%	0.021	0.047		0.019	0.032	0.020	0.012
				40%	0.029	0.029		0.003	0.047	0.017	0.026
			120	0%	0.029	0.052		0.030	0.049	0.014	0.011
				20%	0.018	0.034		0.034	0.016	0.032	0.030
				40%	0.000	0.027		0.047	0.000	0.008	0.014
0.64		15	0%	0.033	0.029	0.014	0.017	0.023	0.012		
			20%	0.038	0.040	0.020	0.018	0.024	0.019		
			40%	0.038	0.022	0.049	0.028	0.028	0.014		
		30	0%	0.033	0.031	0.030	0.034	0.031	0.018		
			20%	0.048	0.029	0.035	0.029	0.038	0.010		
			40%	0.028	0.035	0.013	0.045	0.024	0.012		
		60	0%	0.021	0.036	0.024	0.033	0.039	0.015		
			20%	0.040	0.026	0.019	0.023	0.027	0.017		
			40%	0.021	0.035	0.025	0.025	0.035	0.018		
		120	0%	0.047	0.038	0.029	0.042	0.024	0.010		
			20%	0.033	0.024	0.021	0.024	0.028	0.018		
			40%	0.056	0.035	0.047	0.035	0.021	0.025		

Note: Population value for this parameter is 0. FE = Fixed Effect of Between-Time Random Slope; RE = Random Effect of Between-Time Random Slope; N = Sample Size; T = Measurement Occasions; PMD = Planned-Missing Data Percentage; ω = Reliability. The values represent the rejection averaged across successful replications. Values that were larger than the acceptable upper boundary of rejection (i.e., 0.20) were in bold.

Table 5.43: Rejection of the Fixed Effect of Random Intercept of Y at Between-Individual Level

FE	RE	T	PMD	$\omega = 0.60$			γ_i	$\omega = 0.80$		
				N				N		
				50	100	200		50	100	200
0.3	0.16	15	0%	0.038	0.022	0.027		0.032	0.018	0.011
			20%	0.012	0.034	0.013		0.028	0.016	0.013
			40%	0.018	0.017	0.029		0.038	0.020	0.014
		30	0%	0.028	0.022	0.020		0.040	0.018	0.016
			20%	0.052	0.034	0.024		0.043	0.012	0.016
			40%	0.030	0.017	0.020		0.030	0.014	0.031
		60	0%	0.034	0.030	0.025		0.026	0.012	0.004
			20%	0.048	0.022	0.012		0.028	0.014	0.010
			40%	0.038	0.025	0.013		0.039	0.024	0.012
		120	0%	0.032	0.030	0.024		0.026	0.020	0.018
			20%	0.034	0.022	0.016		0.037	0.020	0.018
			40%	0.036	0.041	0.021		0.035	0.028	0.011
	0.64	15	0%	0.033	0.020	0.026		0.026	0.030	0.019
			20%	0.024	0.025	0.012		0.033	0.022	0.020
			40%	0.033	0.026	0.048		0.037	0.027	0.006
		30	0%	0.038	0.027	0.022		0.029	0.016	0.015
			20%	0.034	0.031	0.021		0.036	0.006	0.031
			40%	0.034	0.035	0.026		0.027	0.024	0.013
		60	0%	0.043	0.020	0.015		0.023	0.024	0.023
			20%	0.041	0.022	0.031		0.045	0.014	0.010
			40%	0.022	0.019	0.027		0.027	0.008	0.011
		120	0%	0.026	0.036	0.024		0.034	0.020	0.026
			20%	0.053	0.046	0.034		0.036	0.016	0.020
			40%	0.046	0.013	0.031		0.043	0.044	0.023
0.6	0.16	15	0%	0.071	0.025	0.024	0.028	0.024	0.013	
			20%	0.026	0.043	0.022	0.033	0.021	0.021	
			40%	0.030	0.028	0.021	0.038	0.020	0.013	
		30	0%	0.038	0.034	0.024	0.034	0.009	0.018	
			20%	0.042	0.013	0.023	0.036	0.027	0.014	
			40%	0.025	0.032	0.026	0.025	0.023	0.008	
		60	0%	0.041	0.025	0.035	0.024	0.010	0.008	
			20%	0.036	0.031	0.022	0.040	0.013	0.012	
			40%	0.039	0.021	0.021	0.058	0.024	0.012	
		120	0%	0.029	0.037	0.028	0.039	0.022	0.017	
			20%	0.033	0.034	0.028	0.014	0.030	0.032	
			40%	0.000	0.025	0.030	0.000	0.021	0.023	
	0.64	15	0%	0.035	0.022	0.022	0.041	0.014	0.018	
			20%	0.035	0.035	0.020	0.023	0.022	0.008	
			40%	0.026	0.032	0.027	0.045	0.013	0.021	
		30	0%	0.042	0.029	0.032	0.023	0.031	0.020	
			20%	0.056	0.035	0.016	0.046	0.033	0.020	
			40%	0.037	0.040	0.020	0.043	0.019	0.009	
		60	0%	0.042	0.025	0.028	0.025	0.027	0.007	
			20%	0.040	0.024	0.026	0.033	0.019	0.011	
			40%	0.031	0.024	0.033	0.031	0.026	0.012	
		120	0%	0.033	0.038	0.019	0.014	0.030	0.017	
			20%	0.037	0.030	0.031	0.037	0.020	0.014	
			40%	0.066	0.038	0.022	0.033	0.032	0.020	

Note: Population value for this parameter is 0. FE = Fixed Effect of Between-Time Random Slope; RE = Random Effect of Between-Time Random Slope; N = Sample Size; T = Measurement Occasions; PMD = Planned-Missing Data Percentage; ω = Reliability. The values represent the rejection averaged across successful replications. Values that were larger than the acceptable upper boundary of rejection (i.e., 0.20) were in bold.

Table 5.44: Descriptive Statistics for Random Effect of Random Intercept of X at Between-Individual Level

FE	RE	T	PMD	$\omega = 0.60$			$\omega = 0.80$			
				50	N 100	200	50	N 100	200	
0.3	0.16	15	0%	3.170 (0.742)	3.170 (0.478)	3.100 (0.328)	$\sigma_{\xi_{X_i}}^2$	1.490 (0.357)	1.460 (0.227)	1.460 (0.158)
			20%	3.340 (0.783)	3.280 (0.496)	3.260 (0.345)		1.560 (0.376)	1.540 (0.240)	1.500 (0.163)
			40%	3.530 (0.826)	3.520 (0.532)	3.460 (0.366)		1.660 (0.396)	1.620 (0.252)	1.600 (0.174)
		30	0%	3.200 (0.708)	3.240 (0.482)	3.160 (0.327)		1.550 (0.347)	1.530 (0.230)	1.490 (0.156)
			20%	3.360 (0.745)	3.370 (0.503)	3.280 (0.340)		1.570 (0.353)	1.560 (0.235)	1.530 (0.160)
			40%	3.610 (0.800)	3.600 (0.536)	3.510 (0.363)		1.690 (0.378)	1.660 (0.250)	1.620 (0.170)
		60	0%	3.320 (0.738)	3.260 (0.485)	3.090 (0.321)		1.580 (0.354)	1.530 (0.229)	1.480 (0.155)
			20%	3.490 (0.776)	3.350 (0.499)	3.240 (0.337)		1.630 (0.364)	1.580 (0.237)	1.520 (0.159)
			40%	3.640 (0.809)	3.560 (0.530)	3.460 (0.360)		1.720 (0.385)	1.650 (0.247)	1.620 (0.170)
		120	0%	3.300 (0.711)	3.200 (0.477)	3.190 (0.333)		1.580 (0.342)	1.510 (0.226)	1.520 (0.159)
			20%	3.500 (0.755)	3.340 (0.498)	3.300 (0.345)		1.630 (0.353)	1.550 (0.232)	1.560 (0.163)
			40%	3.770 (0.815)	3.560 (0.531)	3.550 (0.370)		1.740 (0.377)	1.660 (0.248)	1.640 (0.172)
	0.64	15	0%	5.330 (1.230)	5.150 (0.762)	5.110 (0.530)	2.290 (0.533)	2.230 (0.334)	2.200 (0.231)	
			20%	5.570 (1.290)	5.320 (0.793)	5.220 (0.546)	2.390 (0.560)	2.250 (0.340)	2.260 (0.239)	
			40%	5.770 (1.340)	5.590 (0.834)	5.580 (0.583)	2.500 (0.584)	2.420 (0.366)	2.410 (0.255)	
		30	0%	5.390 (1.180)	5.240 (0.774)	5.230 (0.538)	2.340 (0.517)	2.290 (0.340)	2.280 (0.235)	
			20%	5.590 (1.230)	5.410 (0.802)	5.460 (0.562)	2.420 (0.536)	2.380 (0.354)	2.360 (0.244)	
			40%	5.890 (1.300)	5.780 (0.857)	5.830 (0.600)	2.570 (0.570)	2.490 (0.371)	2.480 (0.257)	
		60	0%	5.400 (1.190)	5.110 (0.758)	5.290 (0.548)	2.370 (0.525)	2.240 (0.333)	2.270 (0.235)	
			20%	5.720 (1.270)	5.300 (0.788)	5.480 (0.568)	2.400 (0.532)	2.290 (0.341)	2.340 (0.243)	
			40%	6.010 (1.330)	5.490 (0.816)	5.930 (0.615)	2.540 (0.564)	2.440 (0.364)	2.500 (0.259)	
		120	0%	5.360 (1.160)	5.210 (0.775)	5.040 (0.525)	2.320 (0.499)	2.280 (0.339)	2.200 (0.230)	
			20%	5.430 (1.170)	5.420 (0.807)	5.210 (0.543)	2.390 (0.516)	2.360 (0.351)	2.270 (0.237)	
			40%	5.810 (1.250)	5.670 (0.844)	5.440 (0.566)	2.530 (0.546)	2.500 (0.372)	2.420 (0.253)	
0.6	0.16	15	0%	4.310 (1.000)	4.270 (0.639)	4.280 (0.449)	1.870 (0.444)	1.850 (0.284)	1.840 (0.198)	
			20%	4.760 (1.110)	4.570 (0.686)	4.520 (0.476)	2.040 (0.484)	1.960 (0.301)	1.930 (0.208)	
			40%	4.970 (1.160)	4.670 (0.700)	4.840 (0.509)	2.140 (0.506)	2.110 (0.323)	2.050 (0.220)	
		30	0%	4.580 (1.010)	4.500 (0.669)	4.470 (0.461)	1.930 (0.430)	1.950 (0.293)	1.970 (0.205)	
			20%	4.760 (1.050)	4.610 (0.685)	4.630 (0.478)	2.020 (0.450)	2.040 (0.306)	2.040 (0.213)	
			40%	5.190 (1.140)	4.990 (0.741)	4.980 (0.513)	2.280 (0.508)	2.170 (0.325)	2.160 (0.224)	
		60	0%	4.650 (1.030)	4.530 (0.673)	4.450 (0.462)	2.020 (0.449)	2.000 (0.299)	1.990 (0.207)	
			20%	4.820 (1.070)	4.690 (0.698)	4.680 (0.486)	2.070 (0.461)	2.070 (0.310)	2.050 (0.214)	
			40%	5.320 (1.180)	5.070 (0.755)	5.100 (0.530)	2.210 (0.493)	2.240 (0.335)	2.160 (0.225)	
		120	0%	4.440 (0.958)	4.510 (0.671)	4.520 (0.471)	1.970 (0.426)	2.010 (0.301)	1.960 (0.205)	
			20%	5.000 (1.080)	4.580 (0.682)	4.500 (0.469)	2.210 (0.478)	2.040 (0.305)	2.030 (0.212)	
			40%	5.790 (1.260)	5.110 (0.761)	4.780 (0.498)	2.350 (0.510)	2.240 (0.334)	2.230 (0.233)	
	0.64	15	0%	6.510 (1.500)	6.730 (0.995)	6.860 (0.711)	2.720 (0.630)	2.860 (0.426)	2.860 (0.299)	
			20%	6.870 (1.590)	7.060 (1.050)	7.300 (0.762)	2.920 (0.682)	2.950 (0.443)	2.990 (0.315)	
			40%	7.180 (1.660)	6.880 (1.020)	7.430 (0.774)	3.020 (0.704)	3.070 (0.460)	3.090 (0.325)	
		30	0%	7.050 (1.550)	7.010 (1.030)	6.970 (0.715)	2.970 (0.653)	2.910 (0.431)	2.900 (0.299)	
			20%	7.430 (1.630)	7.140 (1.060)	7.200 (0.741)	3.050 (0.673)	3.010 (0.448)	2.990 (0.309)	
			40%	7.280 (1.600)	7.860 (1.160)	7.510 (0.772)	3.160 (0.696)	3.090 (0.459)	3.040 (0.314)	
		60	0%	7.090 (1.570)	6.820 (1.010)	6.780 (0.702)	3.070 (0.680)	2.920 (0.433)	2.810 (0.291)	
			20%	7.540 (1.670)	7.260 (1.080)	6.960 (0.721)	3.120 (0.692)	2.970 (0.442)	2.940 (0.305)	
			40%	7.520 (1.660)	7.460 (1.110)	7.580 (0.786)	3.230 (0.717)	3.080 (0.458)	2.920 (0.304)	
		120	0%	7.280 (1.570)	6.970 (1.040)	7.120 (0.741)	3.030 (0.652)	2.920 (0.434)	2.970 (0.310)	
			20%	7.620 (1.640)	7.320 (1.090)	7.430 (0.775)	3.120 (0.673)	3.010 (0.448)	3.080 (0.322)	
			40%	6.700 (1.440)	7.070 (1.050)	7.500 (0.781)	3.200 (0.691)	3.080 (0.459)	3.160 (0.330)	

Note: Population value for this parameter is 0.50. FE = Fixed Effect of Between-Time Random Slope; RE = Random Effect of Between-Time Random Slope; N = Sample Size; T = Measurement Occasions; PMD = Planned-Missing Data Percentage; ω = Reliability. The values outside the brackets represent the average point-estimate of the parameter across the successful replications. The values enclosed in the brackets represent the average standard deviation of the posterior distribution of the parameter across the successful replications.

Table 5.45: Descriptive Statistics for Random Effect of Random Intercept of M at Between-Individual Level

FE	RE	T	PMD	$\omega = 0.60$			$\omega = 0.80$		
				50	N 100	200	50	N 100	200
0.3	0.16	15	0%	3.250 (0.721)	3.150 (0.485)	3.060 (0.317)	$\sigma_{\xi_{M_i}}^2$ 1.500 (0.347)	1.470 (0.235)	1.430 (0.153)
			20%	3.410 (0.760)	3.360 (0.519)	3.280 (0.340)	1.590 (0.366)	1.560 (0.250)	1.500 (0.162)
			40%	3.600 (0.799)	3.530 (0.544)	3.460 (0.358)	1.670 (0.383)	1.620 (0.258)	1.580 (0.169)
		30	0%	3.240 (0.743)	3.240 (0.485)	3.150 (0.328)	1.560 (0.365)	1.520 (0.232)	1.480 (0.157)
			20%	3.470 (0.796)	3.390 (0.508)	3.260 (0.339)	1.590 (0.372)	1.580 (0.241)	1.540 (0.163)
			40%	3.660 (0.841)	3.650 (0.546)	3.520 (0.366)	1.690 (0.392)	1.660 (0.253)	1.610 (0.170)
		60	0%	3.300 (0.745)	3.270 (0.487)	3.140 (0.319)	1.570 (0.357)	1.520 (0.228)	1.480 (0.152)
			20%	3.450 (0.781)	3.330 (0.497)	3.240 (0.330)	1.610 (0.366)	1.570 (0.236)	1.530 (0.157)
			40%	3.610 (0.816)	3.540 (0.527)	3.480 (0.354)	1.670 (0.381)	1.660 (0.249)	1.620 (0.165)
		120	0%	3.280 (0.722)	3.180 (0.462)	3.200 (0.324)	1.570 (0.347)	1.500 (0.219)	1.510 (0.154)
			20%	3.480 (0.767)	3.390 (0.492)	3.340 (0.338)	1.610 (0.355)	1.550 (0.226)	1.560 (0.158)
			40%	3.730 (0.822)	3.590 (0.521)	3.560 (0.361)	1.700 (0.376)	1.660 (0.242)	1.660 (0.168)
	0.64	15	0%	5.450 (1.190)	5.050 (0.762)	5.230 (0.530)	2.340 (0.518)	2.190 (0.336)	2.220 (0.229)
			20%	5.710 (1.250)	5.260 (0.802)	5.530 (0.566)	2.400 (0.537)	2.250 (0.349)	2.350 (0.244)
			40%	5.840 (1.280)	5.530 (0.841)	5.850 (0.598)	2.540 (0.568)	2.420 (0.375)	2.490 (0.259)
		30	0%	5.510 (1.250)	5.140 (0.762)	5.070 (0.522)	2.380 (0.545)	2.260 (0.337)	2.230 (0.231)
			20%	5.810 (1.320)	5.420 (0.807)	5.370 (0.555)	2.480 (0.571)	2.330 (0.349)	2.330 (0.243)
			40%	6.130 (1.400)	5.720 (0.851)	5.810 (0.601)	2.610 (0.600)	2.430 (0.365)	2.400 (0.250)
		60	0%	5.410 (1.220)	5.010 (0.742)	5.180 (0.524)	2.370 (0.534)	2.200 (0.327)	2.250 (0.229)
			20%	5.570 (1.250)	5.220 (0.776)	5.380 (0.544)	2.400 (0.543)	2.270 (0.338)	2.320 (0.236)
			40%	5.950 (1.340)	5.580 (0.829)	5.800 (0.587)	2.490 (0.563)	2.420 (0.361)	2.450 (0.249)
		120	0%	5.320 (1.170)	5.120 (0.741)	5.080 (0.513)	2.340 (0.516)	2.250 (0.326)	2.230 (0.225)
			20%	5.440 (1.200)	5.340 (0.774)	5.320 (0.537)	2.360 (0.520)	2.330 (0.339)	2.300 (0.233)
			40%	5.970 (1.320)	5.530 (0.801)	5.550 (0.561)	2.520 (0.556)	2.450 (0.356)	2.460 (0.249)
0.6	0.16	15	0%	4.280 (0.949)	4.190 (0.644)	4.220 (0.436)	1.800 (0.414)	1.810 (0.290)	1.790 (0.192)
			20%	4.660 (1.040)	4.550 (0.702)	4.520 (0.468)	1.980 (0.456)	1.920 (0.309)	1.870 (0.201)
			40%	5.070 (1.120)	4.550 (0.700)	4.740 (0.490)	2.070 (0.475)	2.030 (0.324)	2.000 (0.215)
		30	0%	4.540 (1.040)	4.460 (0.666)	4.500 (0.467)	1.960 (0.455)	1.900 (0.289)	1.970 (0.208)
			20%	4.890 (1.120)	4.660 (0.698)	4.760 (0.495)	2.010 (0.468)	2.040 (0.311)	2.050 (0.217)
			40%	5.220 (1.200)	5.010 (0.749)	5.050 (0.524)	2.250 (0.523)	2.140 (0.325)	2.150 (0.227)
		60	0%	4.620 (1.040)	4.530 (0.673)	4.490 (0.455)	1.990 (0.453)	2.000 (0.300)	2.010 (0.205)
			20%	4.850 (1.100)	4.690 (0.699)	4.710 (0.478)	2.080 (0.475)	2.070 (0.310)	2.060 (0.211)
			40%	5.440 (1.230)	5.080 (0.756)	5.120 (0.520)	2.250 (0.512)	2.240 (0.336)	2.170 (0.222)
		120	0%	4.360 (0.961)	4.510 (0.654)	4.530 (0.458)	1.960 (0.433)	2.010 (0.292)	1.980 (0.201)
			20%	4.970 (1.100)	4.540 (0.659)	4.580 (0.464)	2.210 (0.488)	2.060 (0.300)	2.040 (0.207)
			40%	6.520 (1.480)	5.140 (0.747)	4.820 (0.487)	1.960 (0.439)	2.240 (0.326)	2.220 (0.226)
	0.64	15	0%	6.500 (1.410)	6.570 (0.989)	6.980 (0.706)	2.650 (0.586)	2.790 (0.427)	2.880 (0.295)
			20%	6.950 (1.530)	7.050 (1.070)	7.500 (0.767)	2.880 (0.643)	2.900 (0.449)	3.060 (0.317)
			40%	6.970 (1.530)	6.920 (1.050)	7.670 (0.783)	3.010 (0.672)	2.990 (0.462)	3.120 (0.323)
		30	0%	6.900 (1.570)	6.900 (1.020)	6.970 (0.717)	2.890 (0.661)	2.870 (0.428)	2.920 (0.302)
			20%	7.260 (1.660)	7.150 (1.060)	7.200 (0.745)	2.990 (0.687)	2.970 (0.444)	3.010 (0.313)
			40%	7.060 (1.610)	7.840 (1.170)	7.900 (0.816)	3.070 (0.705)	3.010 (0.452)	3.200 (0.333)
		60	0%	6.960 (1.560)	6.620 (0.981)	6.990 (0.706)	3.030 (0.684)	2.810 (0.418)	2.890 (0.293)
			20%	7.470 (1.680)	7.020 (1.040)	7.250 (0.734)	3.100 (0.701)	2.850 (0.425)	3.030 (0.308)
			40%	7.320 (1.650)	7.520 (1.120)	8.380 (0.848)	3.240 (0.733)	3.000 (0.447)	3.120 (0.317)
		120	0%	7.310 (1.610)	6.900 (1.000)	7.330 (0.739)	3.060 (0.674)	2.860 (0.416)	3.060 (0.309)
			20%	7.460 (1.640)	7.160 (1.040)	7.580 (0.766)	3.120 (0.688)	2.960 (0.430)	3.150 (0.318)
			40%	6.920 (1.520)	6.780 (0.983)	7.560 (0.763)	3.300 (0.727)	3.080 (0.446)	3.230 (0.327)

Note: Population value for this parameter is 0.50. FE = Fixed Effect of Between-Time Random Slope; RE = Random Effect of Between-Time Random Slope; N = Sample Size; T = Measurement Occasions; PMD = Planned-Missing Data Percentage; ω = Reliability. The values outside the brackets represent the average point-estimate of the parameter across the successful replications. The values enclosed in the brackets represent the average standard deviation of the posterior distribution of the parameter across the successful replications.

Table 5.46: Descriptive Statistics for Random Effect of Random Intercept of Y at Between-Individual Level

FE	RE	T	PMD	$\omega = 0.60$			$\omega = 0.80$			
				50	N 100	200	50	N 100	200	
0.3	0.16	15	0%	3.180 (0.740)	3.080 (0.489)	3.040 (0.330)	$\sigma_{\zeta_{vi}}^2$	1.460 (0.361)	1.430 (0.239)	1.430 (0.162)
			20%	3.350 (0.780)	3.240 (0.513)	3.260 (0.353)		1.570 (0.384)	1.510 (0.251)	1.500 (0.170)
			40%	3.570 (0.828)	3.480 (0.552)	3.440 (0.372)		1.650 (0.401)	1.600 (0.264)	1.590 (0.179)
		30	0%	3.250 (0.738)	3.220 (0.501)	3.150 (0.324)		1.530 (0.356)	1.520 (0.241)	1.480 (0.156)
			20%	3.450 (0.783)	3.320 (0.517)	3.280 (0.337)		1.570 (0.365)	1.560 (0.248)	1.530 (0.161)
			40%	3.730 (0.845)	3.570 (0.556)	3.560 (0.366)		1.720 (0.397)	1.660 (0.264)	1.630 (0.171)
		60	0%	3.260 (0.729)	3.290 (0.493)	3.120 (0.334)		1.560 (0.353)	1.520 (0.231)	1.480 (0.161)
			20%	3.500 (0.781)	3.300 (0.496)	3.260 (0.349)		1.620 (0.365)	1.580 (0.239)	1.530 (0.166)
			40%	3.650 (0.815)	3.560 (0.535)	3.520 (0.376)		1.690 (0.381)	1.660 (0.251)	1.640 (0.177)
		120	0%	3.290 (0.736)	3.190 (0.473)	3.190 (0.324)		1.570 (0.354)	1.530 (0.228)	1.520 (0.156)
			20%	3.530 (0.790)	3.340 (0.494)	3.310 (0.336)		1.580 (0.356)	1.560 (0.231)	1.550 (0.159)
			40%	3.790 (0.848)	3.590 (0.533)	3.560 (0.362)		1.740 (0.390)	1.670 (0.249)	1.650 (0.168)
0.64	0.64	15	0%	5.340 (1.220)	5.060 (0.788)	5.070 (0.541)	2.270 (0.536)	2.180 (0.351)	2.170 (0.238)	
			20%	5.560 (1.280)	5.300 (0.832)	5.330 (0.574)	2.420 (0.578)	2.240 (0.365)	2.260 (0.251)	
			40%	6.030 (1.390)	5.780 (0.909)	5.650 (0.609)	2.560 (0.614)	2.430 (0.396)	2.420 (0.268)	
		30	0%	5.460 (1.230)	5.220 (0.806)	5.130 (0.522)	2.370 (0.542)	2.280 (0.357)	2.240 (0.232)	
			20%	5.740 (1.300)	5.480 (0.850)	5.390 (0.552)	2.460 (0.564)	2.350 (0.369)	2.300 (0.240)	
			40%	6.080 (1.380)	5.840 (0.906)	5.750 (0.589)	2.640 (0.606)	2.540 (0.400)	2.430 (0.253)	
		60	0%	5.420 (1.210)	5.160 (0.770)	5.320 (0.567)	2.410 (0.541)	2.270 (0.341)	2.280 (0.245)	
			20%	5.690 (1.270)	5.390 (0.808)	5.450 (0.583)	2.430 (0.546)	2.330 (0.351)	2.350 (0.252)	
			40%	6.050 (1.350)	5.720 (0.856)	5.960 (0.638)	2.550 (0.573)	2.480 (0.375)	2.490 (0.268)	
		120	0%	5.390 (1.200)	5.280 (0.782)	5.090 (0.515)	2.340 (0.524)	2.310 (0.342)	2.240 (0.228)	
			20%	5.470 (1.220)	5.560 (0.824)	5.310 (0.539)	2.410 (0.541)	2.380 (0.354)	2.290 (0.234)	
			40%	6.050 (1.350)	5.800 (0.860)	5.440 (0.553)	2.600 (0.583)	2.520 (0.375)	2.450 (0.250)	
0.6	0.16	15	0%	4.130 (0.977)	4.220 (0.679)	4.160 (0.459)	1.730 (0.444)	1.810 (0.315)	1.740 (0.207)	
			20%	4.690 (1.100)	4.560 (0.730)	4.490 (0.490)	1.990 (0.504)	1.910 (0.330)	1.870 (0.219)	
			40%	5.000 (1.180)	4.710 (0.759)	4.670 (0.517)	2.040 (0.514)	2.060 (0.356)	1.950 (0.230)	
		30	0%	4.620 (1.050)	4.450 (0.698)	4.440 (0.460)	1.930 (0.455)	1.890 (0.306)	1.960 (0.211)	
			20%	4.700 (1.070)	4.600 (0.719)	4.690 (0.485)	1.970 (0.464)	2.030 (0.327)	2.030 (0.217)	
			40%	5.340 (1.220)	4.900 (0.769)	4.950 (0.515)	2.250 (0.532)	2.140 (0.347)	2.140 (0.230)	
		60	0%	4.520 (1.010)	4.560 (0.685)	4.400 (0.473)	1.970 (0.448)	1.980 (0.302)	1.950 (0.213)	
			20%	4.740 (1.060)	4.760 (0.716)	4.600 (0.494)	2.070 (0.472)	2.090 (0.319)	2.010 (0.220)	
			40%	5.320 (1.190)	5.050 (0.761)	4.990 (0.537)	2.180 (0.497)	2.220 (0.339)	2.100 (0.230)	
		120	0%	4.300 (0.962)	4.480 (0.666)	4.460 (0.454)	2.020 (0.455)	2.030 (0.304)	1.960 (0.201)	
			20%	4.960 (1.110)	4.610 (0.685)	4.580 (0.466)	2.200 (0.497)	2.060 (0.307)	2.040 (0.209)	
			40%	6.510 (1.440)	5.190 (0.771)	4.800 (0.489)	2.090 (0.466)	2.260 (0.338)	2.180 (0.225)	
0.64	0.64	15	0%	6.710 (1.530)	6.600 (1.030)	6.460 (0.690)	2.750 (0.656)	2.770 (0.450)	2.660 (0.295)	
			20%	7.140 (1.650)	6.940 (1.100)	6.870 (0.742)	2.940 (0.712)	2.860 (0.471)	2.830 (0.318)	
			40%	7.230 (1.690)	6.740 (1.070)	7.200 (0.786)	3.130 (0.762)	2.960 (0.492)	2.910 (0.330)	
		30	0%	6.980 (1.570)	6.880 (1.060)	7.090 (0.722)	2.900 (0.664)	2.880 (0.452)	2.970 (0.308)	
			20%	7.230 (1.640)	7.180 (1.120)	7.310 (0.750)	3.010 (0.695)	2.990 (0.473)	3.060 (0.320)	
			40%	7.270 (1.650)	7.810 (1.220)	8.140 (0.837)	3.100 (0.720)	3.140 (0.497)	3.320 (0.349)	
		60	0%	7.160 (1.590)	6.900 (1.030)	6.910 (0.737)	3.030 (0.680)	2.930 (0.441)	2.850 (0.307)	
			20%	7.490 (1.670)	7.370 (1.100)	7.170 (0.767)	3.130 (0.706)	3.010 (0.455)	3.000 (0.324)	
			40%	7.800 (1.740)	7.640 (1.150)	8.270 (0.886)	3.240 (0.732)	3.150 (0.478)	3.040 (0.330)	
		120	0%	7.110 (1.590)	6.920 (1.020)	7.210 (0.731)	2.870 (0.643)	2.880 (0.428)	3.020 (0.307)	
			20%	7.380 (1.650)	7.160 (1.060)	7.470 (0.758)	3.050 (0.685)	2.960 (0.440)	3.140 (0.320)	
			40%	6.820 (1.530)	6.920 (1.030)	7.520 (0.765)	3.160 (0.710)	3.070 (0.457)	3.120 (0.319)	

Note: Population value for this parameter is 0.50. FE = Fixed Effect of Between-Time Random Slope; RE = Random Effect of Between-Time Random Slope; N = Sample Size; T = Measurement Occasions; PMD = Planned-Missing Data Percentage; ω = Reliability. The values outside the brackets represent the average point-estimate of the parameter across the successful replications. The values enclosed in the brackets represent the average standard deviation of the posterior distribution of the parameter across the successful replications.

Table 5.47: Relative Bias of the Random Effect of Random Intercept of X at Between-Individual Level

FE	RE	T	PMD	$\omega = 0.60$			$\omega = 0.80$		
				50	100	200	50	100	200
0.3	0.16	15	0%	5.340	5.340	5.200	1.980	1.910	1.910
			20%	5.680	5.550	5.520	2.130	2.080	2.000
			40%	6.050	6.050	5.910	2.310	2.250	2.210
		30	0%	5.400	5.480	5.320	2.100	2.060	1.970
			20%	5.730	5.740	5.560	2.140	2.120	2.060
			40%	6.230	6.190	6.020	2.380	2.320	2.250
		60	0%	5.650	5.520	5.180	2.160	2.050	1.960
			20%	5.990	5.700	5.480	2.260	2.160	2.050
			40%	6.280	6.120	5.930	2.440	2.290	2.250
		120	0%	5.590	5.400	5.380	2.160	2.020	2.030
			20%	5.990	5.680	5.600	2.260	2.100	2.120
			40%	6.550	6.120	6.100	2.480	2.320	2.290
	0.64	15	0%	9.660	9.290	9.210	3.580	3.460	3.390
			20%	10.100	9.630	9.440	3.790	3.510	3.520
			40%	10.500	10.200	10.200	3.990	3.850	3.820
		30	0%	9.780	9.470	9.470	3.690	3.580	3.560
			20%	10.200	9.820	9.920	3.850	3.750	3.720
			40%	10.800	10.600	10.700	4.150	3.980	3.960
		60	0%	9.800	9.210	9.580	3.740	3.480	3.540
			20%	10.400	9.600	9.960	3.790	3.580	3.680
			40%	11.000	9.980	10.900	4.080	3.890	3.990
		120	0%	9.730	9.420	9.080	3.630	3.560	3.400
			20%	9.870	9.840	9.410	3.780	3.710	3.550
			40%	10.600	10.300	9.870	4.060	3.990	3.840
0.6	0.16	15	0%	7.610	7.540	7.560	2.750	2.690	2.670
			20%	8.520	8.130	8.040	3.080	2.910	2.850
			40%	8.930	8.330	8.680	3.270	3.220	3.090
		30	0%	8.160	8.010	7.950	2.850	2.900	2.940
			20%	8.520	8.210	8.250	3.040	3.080	3.080
			40%	9.380	8.970	8.950	3.560	3.340	3.310
		60	0%	8.310	8.050	7.900	3.030	3.010	2.970
			20%	8.650	8.380	8.370	3.130	3.140	3.110
			40%	9.640	9.150	9.200	3.420	3.480	3.320
		120	0%	7.880	8.010	8.040	2.940	3.030	2.920
			20%	9.000	8.150	8.000	3.420	3.090	3.060
			40%	10.600	9.220	8.560	3.710	3.470	3.450
	0.64	15	0%	12.000	12.500	12.700	4.430	4.720	4.710
			20%	12.700	13.100	13.600	4.840	4.900	4.980
			40%	13.400	12.800	13.900	5.040	5.140	5.180
		30	0%	13.100	13.000	12.900	4.930	4.820	4.800
			20%	13.900	13.300	13.400	5.100	5.030	4.980
			40%	13.600	14.700	14.000	5.320	5.180	5.090
		60	0%	13.200	12.600	12.600	5.140	4.830	4.610
			20%	14.100	13.500	12.900	5.240	4.940	4.880
			40%	14.000	13.900	14.200	5.470	5.160	4.850
		120	0%	13.600	12.900	13.200	5.050	4.840	4.940
			20%	14.200	13.600	13.900	5.240	5.020	5.160
			40%	12.400	13.100	14.000	5.400	5.170	5.330

Note: Population value for this parameter is 0.50. FE = Fixed Effect of Between-Time Random Slope; RE = Random Effect of Between-Time Random Slope; N = Sample Size; T = Measurement Occasions; PMD = Planned-Missing Data Percentage; ω = Reliability. The values represent mean parameter relative bias averaged across successful replications. Values that were not within the acceptable [-0.05 and 0.05] bound were in bold.

Table 5.48: Relative Bias of the Random Effect of Random Intercept of M at Between-Individual Level

FE	RE	T	PMD	$\omega = 0.60$			$\omega = 0.80$		
				50	N 100	200	50	N 100	200
0.3	0.16	15	0%	5.490	5.300	5.120	2.010	1.940	1.860
			20%	5.820	5.720	5.560	2.180	2.120	2.010
			40%	6.200	6.070	5.920	2.330	2.230	2.150
		30	0%	5.480	5.480	5.310	2.130	2.050	1.970
			20%	5.940	5.770	5.520	2.190	2.160	2.080
			40%	6.330	6.300	6.050	2.370	2.330	2.220
		60	0%	5.590	5.530	5.280	2.140	2.040	1.970
			20%	5.910	5.670	5.490	2.210	2.140	2.060
			40%	6.230	6.080	5.960	2.350	2.320	2.230
		120	0%	5.560	5.370	5.400	2.140	2.000	2.030
			20%	5.960	5.780	5.670	2.220	2.100	2.120
			40%	6.460	6.180	6.130	2.410	2.320	2.320
	0.64	15	0%	9.900	9.100	9.460	3.680	3.380	3.440
			20%	10.400	9.530	10.100	3.800	3.500	3.700
			40%	10.700	10.100	10.700	4.090	3.840	3.980
		30	0%	10.000	9.270	9.150	3.770	3.520	3.460
			20%	10.600	9.830	9.740	3.970	3.660	3.660
			40%	11.300	10.400	10.600	4.230	3.860	3.800
		60	0%	9.820	9.010	9.370	3.740	3.390	3.510
			20%	10.100	9.450	9.750	3.800	3.540	3.640
			40%	10.900	10.200	10.600	3.980	3.840	3.890
		120	0%	9.640	9.230	9.160	3.680	3.500	3.450
			20%	9.880	9.680	9.640	3.720	3.660	3.600
			40%	10.900	10.100	10.100	4.040	3.910	3.930
0.6	0.16	15	0%	7.560	7.380	7.450	2.600	2.630	2.590
			20%	8.320	8.100	8.030	2.960	2.850	2.740
			40%	9.130	8.090	8.470	3.140	3.060	3.010
		30	0%	8.080	7.910	8.000	2.910	2.800	2.940
			20%	8.780	8.330	8.520	3.020	3.090	3.110
			40%	9.440	9.010	9.090	3.500	3.280	3.310
		60	0%	8.240	8.050	7.970	2.980	3.000	3.020
			20%	8.700	8.380	8.420	3.170	3.130	3.120
			40%	9.870	9.150	9.240	3.500	3.480	3.340
		120	0%	7.730	8.020	8.060	2.920	3.010	2.950
			20%	8.950	8.070	8.170	3.420	3.120	3.070
			40%	12.000	9.290	8.630	2.920	3.470	3.450
	0.64	15	0%	12.000	12.100	13.000	4.300	4.590	4.750
			20%	12.900	13.100	14.000	4.760	4.810	5.110
			40%	12.900	12.800	14.300	5.020	4.980	5.230
		30	0%	12.800	12.800	12.900	4.790	4.740	4.840
			20%	13.500	13.300	13.400	4.980	4.930	5.020
			40%	13.100	14.700	14.800	5.140	5.030	5.400
		60	0%	12.900	12.200	13.000	5.060	4.620	4.780
			20%	13.900	13.000	13.500	5.200	4.710	5.060
			40%	13.600	14.000	15.800	5.490	5.000	5.240
		120	0%	13.600	12.800	13.700	5.120	4.730	5.120
			20%	13.900	13.300	14.200	5.240	4.920	5.300
			40%	12.800	12.600	14.100	5.600	5.150	5.460

Note: Population value for this parameter is 0.50. FE = Fixed Effect of Between-Time Random Slope; RE = Random Effect of Between-Time Random Slope; N = Sample Size; T = Measurement Occasions; PMD = Planned-Missing Data Percentage; ω = Reliability. The values represent mean parameter relative bias averaged across successful replications. Values that were not within the acceptable [-0.05 and 0.05] bound were in bold.

Table 5.49: Relative Bias of the Random Effect of Random Intercept of Y at Between-Individual Level

FE	RE	T	PMD	$\omega = 0.60$			$\omega = 0.80$		
				50	N 100	200	50	N 100	200
0.3	0.16	15	0%	5.350	5.160	5.070	1.930	1.860	1.860
			20%	5.710	5.470	5.520	2.140	2.020	2.000
			40%	6.140	5.970	5.880	2.290	2.190	2.180
		30	0%	5.510	5.440	5.300	2.070	2.030	1.960
			20%	5.900	5.640	5.560	2.140	2.110	2.060
			40%	6.460	6.150	6.120	2.430	2.320	2.260
		60	0%	5.520	5.570	5.240	2.120	2.040	1.970
			20%	5.990	5.610	5.510	2.230	2.150	2.060
			40%	6.290	6.130	6.030	2.370	2.310	2.280
		120	0%	5.580	5.380	5.390	2.150	2.060	2.040
			20%	6.070	5.670	5.620	2.160	2.110	2.100
			40%	6.590	6.190	6.120	2.470	2.340	2.290
	0.64	15	0%	9.690	9.120	9.150	3.530	3.350	3.330
			20%	10.100	9.590	9.660	3.840	3.480	3.520
			40%	11.100	10.500	10.300	4.130	3.850	3.840
		30	0%	9.920	9.450	9.260	3.750	3.560	3.480
			20%	10.500	9.970	9.780	3.910	3.690	3.600
			40%	11.200	10.700	10.500	4.270	4.080	3.850
		60	0%	9.850	9.310	9.640	3.830	3.530	3.560
			20%	10.400	9.790	9.910	3.860	3.650	3.690
			40%	11.100	10.400	10.900	4.100	3.960	3.980
		120	0%	9.790	9.560	9.170	3.680	3.620	3.490
			20%	9.940	10.100	9.620	3.830	3.770	3.590
			40%	11.100	10.600	9.890	4.200	4.050	3.900
0.6	0.16	15	0%	7.260	7.440	7.310	2.460	2.610	2.480
			20%	8.380	8.110	7.970	2.980	2.820	2.750
			40%	9.010	8.420	8.340	3.070	3.130	2.900
		30	0%	8.240	7.900	7.880	2.860	2.780	2.910
			20%	8.400	8.200	8.390	2.930	3.060	3.050
			40%	9.680	8.800	8.910	3.500	3.290	3.280
		60	0%	8.040	8.110	7.800	2.930	2.950	2.900
			20%	8.470	8.520	8.200	3.140	3.180	3.030
			40%	9.630	9.110	8.970	3.360	3.430	3.200
		120	0%	7.590	7.960	7.910	3.040	3.060	2.910
			20%	8.920	8.230	8.150	3.410	3.110	3.080
			40%	12.000	9.380	8.590	3.170	3.510	3.370
	0.64	15	0%	12.400	12.200	11.900	4.500	4.550	4.310
			20%	13.300	12.900	12.700	4.890	4.720	4.660
			40%	13.500	12.500	13.400	5.260	4.920	4.820
		30	0%	13.000	12.800	13.200	4.800	4.760	4.930
			20%	13.500	13.400	13.600	5.020	4.980	5.120
			40%	13.500	14.600	15.300	5.210	5.270	5.650
		60	0%	13.300	12.800	12.800	5.060	4.850	4.710
			20%	14.000	13.700	13.300	5.270	5.020	5.000
			40%	14.600	14.300	15.500	5.480	5.300	5.090
		120	0%	13.200	12.800	13.400	4.740	4.760	5.040
			20%	13.800	13.300	13.900	5.100	4.920	5.270
			40%	12.600	12.800	14.000	5.320	5.130	5.250

Note: Population value for this parameter is 0.50. FE = Fixed Effect of Between-Time Random Slope; RE = Random Effect of Between-Time Random Slope; N = Sample Size; T = Measurement Occasions; PMD = Planned-Missing Data Percentage; ω = Reliability. The values represent mean parameter relative bias averaged across successful replications. Values that were not within the acceptable [-0.05 and 0.05] bound were in bold.

Table 5.50: Coverage of the Random Effect of Random Intercept of X at Between-Individual Level

FE	RE	T	PMD	$\omega = 0.60$			$\sigma_{\xi_i}^2$	$\omega = 0.80$		
				50	N 100	200		50	N 100	200
0.3	0.16	15	0%	0.000	0.000	0.000	0.010	0.000	0.000	0.000
			20%	0.000	0.000	0.000		0.004	0.000	0.000
			40%	0.000	0.000	0.000		0.008	0.000	0.000
		30	0%	0.000	0.000	0.000		0.008	0.000	0.000
			20%	0.000	0.000	0.000		0.004	0.000	0.000
			40%	0.000	0.000	0.000		0.004	0.000	0.000
		60	0%	0.000	0.000	0.000		0.000	0.000	0.000
			20%	0.000	0.000	0.000		0.002	0.000	0.000
			40%	0.000	0.000	0.000		0.002	0.000	0.000
		120	0%	0.000	0.000	0.000		0.004	0.000	0.000
			20%	0.000	0.000	0.000		0.004	0.000	0.000
			40%	0.000	0.000	0.000		0.002	0.000	0.000
	0.64	15	0%	0.000	0.000	0.000		0.004	0.000	0.000
			20%	0.000	0.000	0.000		0.002	0.000	0.000
			40%	0.000	0.000	0.000		0.000	0.000	0.000
		30	0%	0.000	0.000	0.000		0.002	0.000	0.000
			20%	0.000	0.000	0.000		0.000	0.000	0.000
			40%	0.000	0.000	0.000		0.000	0.000	0.000
		60	0%	0.000	0.000	0.000		0.000	0.000	0.000
			20%	0.000	0.000	0.000		0.000	0.000	0.000
			40%	0.000	0.000	0.000		0.000	0.000	0.000
		120	0%	0.000	0.000	0.000		0.003	0.000	0.000
			20%	0.000	0.000	0.000		0.000	0.000	0.000
			40%	0.000	0.000	0.000		0.000	0.000	0.000
0.6	0.16	15	0%	0.000	0.000	0.000	0.000	0.000	0.000	
			20%	0.000	0.000	0.000	0.000	0.000	0.000	
			40%	0.000	0.000	0.000	0.000	0.000	0.000	
		30	0%	0.000	0.000	0.000	0.004	0.000	0.000	
			20%	0.000	0.000	0.000	0.000	0.000	0.000	
			40%	0.000	0.000	0.000	0.000	0.000	0.000	
		60	0%	0.000	0.000	0.000	0.000	0.000	0.000	
			20%	0.000	0.000	0.000	0.000	0.000	0.000	
			40%	0.000	0.000	0.000	0.000	0.000	0.000	
		120	0%	0.000	0.000	0.000	0.000	0.000	0.000	
			20%	0.000	0.000	0.000	0.000	0.000	0.000	
			40%	0.000	0.000	0.000	0.000	0.000	0.000	
	0.64	15	0%	0.000	0.000	0.000	0.000	0.000	0.000	
			20%	0.000	0.000	0.000	0.000	0.000	0.000	
			40%	0.000	0.000	0.000	0.000	0.000	0.000	
		30	0%	0.000	0.000	0.000	0.000	0.000	0.000	
			20%	0.000	0.000	0.000	0.000	0.000	0.000	
			40%	0.000	0.000	0.000	0.000	0.000	0.000	
		60	0%	0.000	0.000	0.000	0.000	0.000	0.000	
			20%	0.000	0.000	0.000	0.000	0.000	0.000	
			40%	0.000	0.000	0.000	0.000	0.000	0.000	
		120	0%	0.000	0.000	0.000	0.002	0.000	0.000	
			20%	0.000	0.000	0.000	0.000	0.000	0.000	
			40%	0.000	0.000	0.000	0.000	0.000	0.000	

Note: Population value for this parameter is 0.50. FE = Fixed Effect of Between-Time Random Slope; RE = Random Effect of Between-Time Random Slope; N = Sample Size; T = Measurement Occasions; PMD = Planned-Missing Data Percentage; ω = Reliability. The values represent the coverage averaged across successful replications. Values that were smaller than the acceptable lower boundary of coverage (i.e., 0.87) were in bold.

Table 5.51: Coverage of the Random Effect of Random Intercept of M at Between-Individual Level

FE	RE	T	PMD	$\omega = 0.60$			$\sigma_{\xi_{M_i}}^2$	$\omega = 0.80$		
				50	N 100	200		50	N 100	200
0.3	0.16	15	0%	0.000	0.000	0.000	0.006	0.006	0.000	0.000
			20%	0.000	0.000	0.000		0.010	0.000	0.000
			40%	0.000	0.000	0.000		0.006	0.000	0.000
		30	0%	0.000	0.000	0.000		0.006	0.000	0.000
			20%	0.000	0.000	0.000		0.012	0.000	0.000
			40%	0.000	0.000	0.000		0.006	0.000	0.000
		60	0%	0.000	0.000	0.000		0.002	0.000	0.000
			20%	0.000	0.000	0.000		0.002	0.000	0.000
			40%	0.000	0.000	0.000		0.000	0.000	0.000
		120	0%	0.000	0.000	0.000		0.000	0.000	0.000
			20%	0.000	0.000	0.000		0.002	0.000	0.000
			40%	0.000	0.000	0.000		0.000	0.000	0.000
	0.64	15	0%	0.000	0.000	0.000	0.000	0.000	0.000	
			20%	0.000	0.000	0.000	0.000	0.000	0.000	
			40%	0.000	0.000	0.000	0.000	0.000	0.000	
		30	0%	0.000	0.000	0.000	0.000	0.000	0.000	
			20%	0.000	0.000	0.000	0.000	0.000	0.000	
			40%	0.000	0.000	0.000	0.002	0.000	0.000	
		60	0%	0.000	0.000	0.000	0.002	0.000	0.000	
			20%	0.000	0.000	0.000	0.002	0.000	0.000	
			40%	0.000	0.000	0.000	0.002	0.000	0.000	
		120	0%	0.000	0.000	0.000	0.000	0.000	0.000	
			20%	0.000	0.000	0.000	0.000	0.000	0.000	
			40%	0.000	0.000	0.000	0.000	0.000	0.000	
0.6	0.16	15	0%	0.000	0.000	0.000	0.003	0.003	0.000	0.000
			20%	0.000	0.000	0.000		0.005	0.000	0.000
			40%	0.000	0.000	0.000		0.000	0.000	0.000
		30	0%	0.000	0.000	0.000		0.004	0.000	0.000
			20%	0.000	0.000	0.000		0.003	0.000	0.000
			40%	0.000	0.000	0.000		0.000	0.000	0.000
		60	0%	0.000	0.000	0.000		0.000	0.000	0.000
			20%	0.000	0.000	0.000		0.000	0.000	0.000
			40%	0.000	0.000	0.000		0.000	0.000	0.000
		120	0%	0.000	0.000	0.000		0.000	0.000	0.000
			20%	0.000	0.000	0.000		0.000	0.000	0.000
			40%	0.000	0.000	0.000		0.000	0.000	0.000
	0.64	15	0%	0.000	0.000	0.000	0.000	0.000	0.000	
			20%	0.000	0.000	0.000	0.000	0.000	0.000	
			40%	0.000	0.000	0.000	0.003	0.000	0.000	
		30	0%	0.000	0.000	0.000	0.000	0.000	0.000	
			20%	0.000	0.000	0.000	0.000	0.000	0.000	
			40%	0.000	0.000	0.000	0.000	0.000	0.000	
		60	0%	0.000	0.000	0.000	0.000	0.000	0.000	
			20%	0.000	0.000	0.000	0.000	0.000	0.000	
			40%	0.000	0.000	0.000	0.000	0.000	0.000	
		120	0%	0.000	0.000	0.000	0.000	0.000	0.000	
			20%	0.000	0.000	0.000	0.000	0.000	0.000	
			40%	0.000	0.000	0.000	0.000	0.000	0.000	

Note: Population value for this parameter is 0.50. FE = Fixed Effect of Between-Time Random Slope; RE = Random Effect of Between-Time Random Slope; N = Sample Size; T = Measurement Occasions; PMD = Planned-Missing Data Percentage; ω = Reliability. The values represent the coverage averaged across successful replications. Values that were smaller than the acceptable lower boundary of coverage (i.e., 0.87) were in bold.

Table 5.52: Coverage of the Random Effect of Random Intercept of Y at Between-Individual Level

FE	RE	T	PMD	$\omega = 0.60$			$\sigma_{\xi_i}^2$	$\omega = 0.80$		
				50	N 100	200		50	N 100	200
0.3	0.16	15	0%	0.000	0.000	0.000	0.032	0.032	0.000	0.000
			20%	0.000	0.000	0.000		0.026	0.000	0.000
			40%	0.000	0.000	0.000		0.022	0.000	0.000
		30	0%	0.000	0.000	0.000		0.010	0.000	0.000
			20%	0.000	0.000	0.000		0.010	0.000	0.000
			40%	0.000	0.000	0.000		0.000	0.000	0.000
		60	0%	0.000	0.000	0.000		0.006	0.000	0.000
			20%	0.000	0.000	0.000		0.002	0.000	0.000
			40%	0.000	0.000	0.000		0.004	0.000	0.000
		120	0%	0.000	0.000	0.000		0.002	0.000	0.000
			20%	0.000	0.000	0.000		0.004	0.000	0.000
			40%	0.000	0.000	0.000		0.004	0.000	0.000
	0.64	15	0%	0.000	0.000	0.000		0.007	0.000	0.000
			20%	0.000	0.000	0.000		0.002	0.000	0.000
			40%	0.000	0.000	0.000		0.007	0.000	0.000
		30	0%	0.000	0.000	0.000		0.000	0.000	0.000
			20%	0.000	0.000	0.000		0.000	0.000	0.000
			40%	0.000	0.000	0.000		0.000	0.000	0.000
		60	0%	0.000	0.000	0.000		0.000	0.000	0.000
			20%	0.000	0.000	0.000		0.000	0.000	0.000
			40%	0.000	0.000	0.000		0.000	0.000	0.000
		120	0%	0.000	0.000	0.000		0.003	0.000	0.000
			20%	0.000	0.000	0.000		0.000	0.000	0.000
			40%	0.000	0.000	0.000		0.002	0.000	0.000
0.6	0.16	15	0%	0.000	0.000	0.000	0.031	0.002	0.000	
			20%	0.000	0.000	0.000	0.016	0.000	0.000	
			40%	0.000	0.000	0.000	0.031	0.000	0.000	
		30	0%	0.000	0.000	0.000	0.013	0.000	0.000	
			20%	0.000	0.000	0.000	0.003	0.000	0.000	
			40%	0.000	0.000	0.000	0.000	0.000	0.000	
		60	0%	0.000	0.000	0.000	0.000	0.000	0.000	
			20%	0.000	0.000	0.000	0.000	0.000	0.000	
			40%	0.000	0.000	0.000	0.000	0.000	0.000	
		120	0%	0.000	0.000	0.000	0.000	0.000	0.000	
			20%	0.000	0.000	0.000	0.002	0.000	0.000	
			40%	0.000	0.000	0.000	0.000	0.000	0.000	
	0.64	15	0%	0.000	0.000	0.000	0.000	0.000	0.000	
			20%	0.000	0.000	0.000	0.000	0.000	0.000	
			40%	0.000	0.000	0.000	0.000	0.000	0.000	
		30	0%	0.000	0.000	0.000	0.005	0.000	0.000	
			20%	0.000	0.000	0.000	0.000	0.000	0.000	
			40%	0.000	0.000	0.000	0.000	0.000	0.000	
		60	0%	0.000	0.000	0.000	0.002	0.000	0.000	
			20%	0.000	0.000	0.000	0.000	0.000	0.000	
			40%	0.000	0.000	0.000	0.002	0.000	0.000	
		120	0%	0.000	0.000	0.000	0.000	0.000	0.000	
			20%	0.000	0.000	0.000	0.000	0.000	0.000	
			40%	0.000	0.000	0.000	0.000	0.000	0.000	

Note: Population value for this parameter is 0.50. FE = Fixed Effect of Between-Time Random Slope; RE = Random Effect of Between-Time Random Slope; N = Sample Size; T = Measurement Occasions; PMD = Planned-Missing Data Percentage; ω = Reliability. The values represent the coverage averaged across successful replications. Values that were smaller than the acceptable lower boundary of coverage (i.e., 0.87) were in bold.

Table 5.53: Rejection of the Random Effect of Random Intercept of X at Between-Individual Level

FE	RE	T	PMD	$\omega = 0.60$			$\sigma_{\xi_{X_i}}^2$	$\omega = 0.80$					
				50	N 100	200		50	N 100	200			
0.3	0.16	15	0%	1.000	1.000	1.000	1.000	1.000	1.000	1.000			
			20%	1.000	1.000	1.000		1.000	1.000	1.000			
			40%	1.000	1.000	1.000		1.000	1.000	1.000			
		30	0%	1.000	1.000	1.000		1.000	1.000	1.000	1.000		
			20%	1.000	1.000	1.000		1.000	1.000	1.000	1.000		
			40%	1.000	1.000	1.000		1.000	1.000	1.000	1.000		
		60	0%	1.000	1.000	1.000		1.000	1.000	1.000	1.000		
			20%	1.000	1.000	1.000		1.000	1.000	1.000	1.000		
			40%	1.000	1.000	1.000		1.000	1.000	1.000	1.000		
		120	0%	1.000	1.000	1.000		1.000	1.000	1.000	1.000		
			20%	1.000	1.000	1.000		1.000	1.000	1.000	1.000		
			40%	1.000	1.000	1.000		1.000	1.000	1.000	1.000		
	0.64	15	0%	1.000	1.000	1.000		1.000	1.000	1.000	1.000		
			20%	1.000	1.000	1.000		1.000	1.000	1.000	1.000		
			40%	1.000	1.000	1.000		1.000	1.000	1.000	1.000		
		30	0%	1.000	1.000	1.000		1.000	1.000	1.000	1.000		
			20%	1.000	1.000	1.000		1.000	1.000	1.000	1.000		
			40%	1.000	1.000	1.000		1.000	1.000	1.000	1.000		
		60	0%	1.000	1.000	1.000		1.000	1.000	1.000	1.000		
			20%	1.000	1.000	1.000		1.000	1.000	1.000	1.000		
			40%	1.000	1.000	1.000		1.000	1.000	1.000	1.000		
		120	0%	1.000	1.000	1.000		1.000	1.000	1.000	1.000		
			20%	1.000	1.000	1.000		1.000	1.000	1.000	1.000		
			40%	1.000	1.000	1.000		1.000	1.000	1.000	1.000		
	0.6	0.16	15	0%	1.000	1.000		1.000	1.000	1.000	1.000	1.000	
				20%	1.000	1.000		1.000		1.000	1.000	1.000	
				40%	1.000	1.000		1.000		1.000	1.000	1.000	
			30	0%	1.000	1.000		1.000		1.000	1.000	1.000	1.000
				20%	1.000	1.000		1.000		1.000	1.000	1.000	1.000
				40%	1.000	1.000		1.000		1.000	1.000	1.000	1.000
			60	0%	1.000	1.000		1.000		1.000	1.000	1.000	1.000
				20%	1.000	1.000		1.000		1.000	1.000	1.000	1.000
				40%	1.000	1.000		1.000		1.000	1.000	1.000	1.000
			120	0%	1.000	1.000		1.000		1.000	1.000	1.000	1.000
				20%	1.000	1.000		1.000		1.000	1.000	1.000	1.000
				40%	1.000	1.000		1.000		1.000	1.000	1.000	1.000
0.64		15	0%	1.000	1.000	1.000	1.000	1.000		1.000	1.000		
			20%	1.000	1.000	1.000	1.000	1.000		1.000	1.000		
			40%	1.000	1.000	1.000	1.000	1.000		1.000	1.000		
		30	0%	1.000	1.000	1.000	1.000	1.000		1.000	1.000		
			20%	1.000	1.000	1.000	1.000	1.000		1.000	1.000		
			40%	1.000	1.000	1.000	1.000	1.000		1.000	1.000		
		60	0%	1.000	1.000	1.000	1.000	1.000		1.000	1.000		
			20%	1.000	1.000	1.000	1.000	1.000		1.000	1.000		
			40%	1.000	1.000	1.000	1.000	1.000		1.000	1.000		
		120	0%	1.000	1.000	1.000	1.000	1.000		1.000	1.000		
			20%	1.000	1.000	1.000	1.000	1.000		1.000	1.000		
			40%	1.000	1.000	1.000	1.000	1.000		1.000	1.000		

Note: Population value for this parameter is 0.50. FE = Fixed Effect of Between-Time Random Slope; RE = Random Effect of Between-Time Random Slope; N = Sample Size; T = Measurement Occasions; PMD = Planned-Missing Data Percentage; ω = Reliability. The values represent the rejection averaged across successful replications. Values that were smaller than the acceptable lower boundary of rejection (i.e., 0.80) were in bold.

Table 5.54: Rejection of the Random Effect of Random Intercept of M at Between-Individual Level

FE	RE	T	PMD	$\omega = 0.60$			$\omega = 0.80$			
				50	100	200	50	100	200	
0.3	0.16	15	0%	1.000	1.000	1.000	1.000	1.000	1.000	
			20%	1.000	1.000	1.000	1.000	1.000	1.000	
			40%	1.000	1.000	1.000	1.000	1.000	1.000	
		30	0%	1.000	1.000	1.000	1.000	1.000	1.000	
			20%	1.000	1.000	1.000	1.000	1.000	1.000	
			40%	1.000	1.000	1.000	1.000	1.000	1.000	
		60	0%	1.000	1.000	1.000	1.000	1.000	1.000	
			20%	1.000	1.000	1.000	1.000	1.000	1.000	
			40%	1.000	1.000	1.000	1.000	1.000	1.000	
		120	0%	1.000	1.000	1.000	1.000	1.000	1.000	
			20%	1.000	1.000	1.000	1.000	1.000	1.000	
			40%	1.000	1.000	1.000	1.000	1.000	1.000	
	0.64	15	0%	1.000	1.000	1.000	1.000	1.000	1.000	
			20%	1.000	1.000	1.000	1.000	1.000	1.000	
			40%	1.000	1.000	1.000	1.000	1.000	1.000	
		30	0%	1.000	1.000	1.000	1.000	1.000	1.000	
			20%	1.000	1.000	1.000	1.000	1.000	1.000	
			40%	1.000	1.000	1.000	1.000	1.000	1.000	
		60	0%	1.000	1.000	1.000	1.000	1.000	1.000	
			20%	1.000	1.000	1.000	1.000	1.000	1.000	
			40%	1.000	1.000	1.000	1.000	1.000	1.000	
		120	0%	1.000	1.000	1.000	1.000	1.000	1.000	
			20%	1.000	1.000	1.000	1.000	1.000	1.000	
			40%	1.000	1.000	1.000	1.000	1.000	1.000	
	0.6	0.16	15	0%	1.000	1.000	1.000	1.000	1.000	1.000
				20%	1.000	1.000	1.000	1.000	1.000	1.000
				40%	1.000	1.000	1.000	1.000	1.000	1.000
			30	0%	1.000	1.000	1.000	1.000	1.000	1.000
				20%	1.000	1.000	1.000	1.000	1.000	1.000
				40%	1.000	1.000	1.000	1.000	1.000	1.000
			60	0%	1.000	1.000	1.000	1.000	1.000	1.000
				20%	1.000	1.000	1.000	1.000	1.000	1.000
				40%	1.000	1.000	1.000	1.000	1.000	1.000
			120	0%	1.000	1.000	1.000	1.000	1.000	1.000
				20%	1.000	1.000	1.000	1.000	1.000	1.000
				40%	1.000	1.000	1.000	1.000	1.000	1.000
0.64		15	0%	1.000	1.000	1.000	1.000	1.000	1.000	
			20%	1.000	1.000	1.000	1.000	1.000	1.000	
			40%	1.000	1.000	1.000	1.000	1.000	1.000	
		30	0%	1.000	1.000	1.000	1.000	1.000	1.000	
			20%	1.000	1.000	1.000	1.000	1.000	1.000	
			40%	1.000	1.000	1.000	1.000	1.000	1.000	
		60	0%	1.000	1.000	1.000	1.000	1.000	1.000	
			20%	1.000	1.000	1.000	1.000	1.000	1.000	
			40%	1.000	1.000	1.000	1.000	1.000	1.000	
		120	0%	1.000	1.000	1.000	1.000	1.000	1.000	
			20%	1.000	1.000	1.000	1.000	1.000	1.000	
			40%	1.000	1.000	1.000	1.000	1.000	1.000	

Note: Population value for this parameter is 0.50. FE = Fixed Effect of Between-Time Random Slope; RE = Random Effect of Between-Time Random Slope; N = Sample Size; T = Measurement Occasions; PMD = Planned-Missing Data Percentage; ω = Reliability. The values represent the rejection averaged across successful replications. Values that were smaller than the acceptable lower boundary of rejection (i.e., 0.80) were in bold.

Table 5.55: Rejection of the Random Effect of Random Intercept of Y at Between-Individual Level

FE	RE	T	PMD	$\omega = 0.60$			$\sigma_{\xi_{vi}}^2$	$\omega = 0.80$					
				50	N 100	200		50	N 100	200			
0.3	0.16	15	0%	1.000	1.000	1.000	1.000	1.000	1.000	1.000			
			20%	1.000	1.000	1.000		1.000	1.000	1.000			
			40%	1.000	1.000	1.000		1.000	1.000	1.000			
		30	0%	1.000	1.000	1.000		1.000	1.000	1.000	1.000		
			20%	1.000	1.000	1.000		1.000	1.000	1.000	1.000		
			40%	1.000	1.000	1.000		1.000	1.000	1.000	1.000		
		60	0%	1.000	1.000	1.000		1.000	1.000	1.000	1.000		
			20%	1.000	1.000	1.000		1.000	1.000	1.000	1.000		
			40%	1.000	1.000	1.000		1.000	1.000	1.000	1.000		
		120	0%	1.000	1.000	1.000		1.000	1.000	1.000	1.000		
			20%	1.000	1.000	1.000		1.000	1.000	1.000	1.000		
			40%	1.000	1.000	1.000		1.000	1.000	1.000	1.000		
	0.64	15	0%	1.000	1.000	1.000		1.000	1.000	1.000	1.000		
			20%	1.000	1.000	1.000		1.000	1.000	1.000	1.000		
			40%	1.000	1.000	1.000		1.000	1.000	1.000	1.000		
		30	0%	1.000	1.000	1.000		1.000	1.000	1.000	1.000		
			20%	1.000	1.000	1.000		1.000	1.000	1.000	1.000		
			40%	1.000	1.000	1.000		1.000	1.000	1.000	1.000		
		60	0%	1.000	1.000	1.000		1.000	1.000	1.000	1.000		
			20%	1.000	1.000	1.000		1.000	1.000	1.000	1.000		
			40%	1.000	1.000	1.000		1.000	1.000	1.000	1.000		
		120	0%	1.000	1.000	1.000		1.000	1.000	1.000	1.000		
			20%	1.000	1.000	1.000		1.000	1.000	1.000	1.000		
			40%	1.000	1.000	1.000		1.000	1.000	1.000	1.000		
	0.6	0.16	15	0%	1.000	1.000		1.000	1.000	1.000	1.000	1.000	
				20%	1.000	1.000		1.000		1.000	1.000	1.000	
				40%	1.000	1.000		1.000		1.000	1.000	1.000	
			30	0%	1.000	1.000		1.000		1.000	1.000	1.000	1.000
				20%	1.000	1.000		1.000		1.000	1.000	1.000	1.000
				40%	1.000	1.000		1.000		1.000	1.000	1.000	1.000
			60	0%	1.000	1.000		1.000		1.000	1.000	1.000	1.000
				20%	1.000	1.000		1.000		1.000	1.000	1.000	1.000
				40%	1.000	1.000		1.000		1.000	1.000	1.000	1.000
			120	0%	1.000	1.000		1.000		1.000	1.000	1.000	1.000
				20%	1.000	1.000		1.000		1.000	1.000	1.000	1.000
				40%	1.000	1.000		1.000		1.000	1.000	1.000	1.000
0.64		15	0%	1.000	1.000	1.000	1.000	1.000		1.000	1.000		
			20%	1.000	1.000	1.000	1.000	1.000		1.000	1.000		
			40%	1.000	1.000	1.000	1.000	1.000		1.000	1.000		
		30	0%	1.000	1.000	1.000	1.000	1.000		1.000	1.000		
			20%	1.000	1.000	1.000	1.000	1.000		1.000	1.000		
			40%	1.000	1.000	1.000	1.000	1.000		1.000	1.000		
		60	0%	1.000	1.000	1.000	1.000	1.000		1.000	1.000		
			20%	1.000	1.000	1.000	1.000	1.000		1.000	1.000		
			40%	1.000	1.000	1.000	1.000	1.000		1.000	1.000		
		120	0%	1.000	1.000	1.000	1.000	1.000		1.000	1.000		
			20%	1.000	1.000	1.000	1.000	1.000		1.000	1.000		
			40%	1.000	1.000	1.000	1.000	1.000		1.000	1.000		

Note: Population value for this parameter is 0.50. FE = Fixed Effect of Between-Time Random Slope; RE = Random Effect of Between-Time Random Slope; N = Sample Size; T = Measurement Occasions; PMD = Planned-Missing Data Percentage; ω = Reliability. The values represent the rejection averaged across successful replications. Values that were smaller than the acceptable lower boundary of rejection (i.e., 0.80) were in bold.

5.5 Summary and Discussion

The objective of this study was to evaluate the key parameters of a time-varying mediation effect model as implemented using a cross-classified model in the Dynamic Structural Equation Model (DSEM) framework in Mplus with data simulated to represent various sample sizes, measurement occasions, effect sizes, degree of planned-missing data and degree of measurement reliability.

The simulation results suggested sample size (N) primarily affected the estimation of the between-individual parameter, especially the variance parameter of the random effect; In contrast, measurement occasion (T) primarily affected the estimation of the between-time parameter, similarly, especially on the variance parameter of the random effect. In particular, the larger the sample size and measurement occasion, the smaller the relative bias the parameter would be. On top of that, a larger sample size and measurement occasion were also associated with a smaller standard deviation of the posterior distribution, implying higher precision in estimate in the form of a narrower HDI.

Due to the current limitation of the Mplus software (v8.3), time-varying relationship between lagged latent variables were unable to be modelled in a cross-classified model. Therefore, when time-varying (random) autoregressive were of interest, instead of lagged *latent* variables, lagged *observed* variables had to be used. This study chose to simulate the common scenario which observed variables are computed using available items in the cases with planned-missing data (*PMD*). The results suggested that this method of treating planned-missing data was not optimal as the conditions involving *PMD* resulted in large parameter relative bias on both between-time and between-individual level. The choice of computing the observed variables used in this study may be the cause of the result. The computation of an observed composite score using available (non-missing) items is equivalent to mean-replacement of the missing data-point using available data-point which may not be a suitable for handling missing data even under the assumption of data missing-completely-at-random (Enders, 2010).

The results suggested that the effect sizes of the fixed effect (mean) and random effect (variance) of the between-time random slope would only likely affect the rejec-

tion of the parameter (i.e., the overlapping between the 90% HDI and ROPE). This was likely due to the fact that a larger effect size is numerically located further away from the null equivalent range which the ROPE defined, therefore, with low estimation bias and reasonable precision of the estimate, a larger effect size resulted in larger rejection.

Reliability (ω) also played a significant role in the parameter estimates. The results suggested that the larger the reliability, the smaller the parameter bias, especially the variance of the random effect on both the between-time and between-individual level. The results also suggested that the unreliability may largely inflate the variance of the between-individual random intercept; essentially causing the true between-individual variability to be conflated with the measurement error variances.

5.6 Limitations and Future Directions

Future research may consider focusing on establishing and evaluating a method to properly handle three-form planned-missing data in the TVEM. One of the methods that could be explored is an alternative modelling framework that incorporates latent measurement model into the time-varying effect model that also allow for the modelling of relationship between lagged latent variables. The use of the measurement model was shown to be a promising methodology to optimally include planned-missing data in the analysis of time-invariant mediation effect in chapter 4. On the other hand, an alternative method for mean-replacement (e.g., multiple imputation) should be explored if observed scores need to be used in the place of latent measurement models.

In contrast to the three-form PMD design, the wave-missing PMD design could be considered when TVEM is the model of interest. I postulate that the wave-missing PMD may result in a better parameter recovery than the three-form PMD because the planned-missing for wave-missing PMD occurs between-wave instead of within-wave in the three-form design. In the wave-missing PMD design, a composite score can be calculated with all available data within each wave, and the between-wave planned-

missing data could still be treated as missing at random in the model.

This study also did not manipulate the effect sizes of the random intercept at the between-time level nor the random slope at the between-individual level as time-varying mediation effect was the focus of the study. Future study could include these experimental factor in order to evaluate and provided relevant suggestions on estimating these parameters.

Lastly, the data-fitting model was an over-specified model for the simulated data using the data-generating model as a reference. Additional parameters were freely estimated in the data-fitting model that was specified as 0 in the data-generating model (i.e., covariance between the within-level disturbances, between-time variance of random intercept, and between-individual variance of random slope, and mean of random intercept). The descriptive statistics of the estimated covariance between the within-level disturbances can be found in section E.3, while the others can be found in this chapter. Unlike in chapter 4 where the over-specified parameters were all close to 0 (i.e., the population value; therefore the impact on the other parameter estimates in the model were unlikely to be large), the over-specified parameters in this study were largely close to 0 (only considering the 0% missing-data condition), except for the between-individual variance of random slope in some condition which showed unexpectedly large estimates particularly at the $FE = 0.60$ conditions. This would likely have an effect on the estimation of the key parameters in those affected replications, hence caution needs to be exercised when interpreting the results in those conditions. A study on the effect of this over-(mis)specification on the model parameters is currently undertaken at the time of writing.

5.7 Recommendations

Based on the results of the current study, I would first suggest *against* applied researcher to implement planned-missing data in a cross-classified model when measurement model cannot be modelled due to software limitations to avoid large parameter

bias. To re-iterate, the current modelling limitation was on the specification of time-varying (random) effect of slope of *lagged-latent* variable in Mplus v8.3. However, if the relationship between lagged-latent variable is not a requirement in the model specification, the random effect of time between latent variables can still be estimated in Mplus [see Asparouhov et al. (2018) for a detailed description of limitations].

If testing time-varying effect is the focus of the research, I would suggest applied researcher to maximise the resources on increasing the measurement occasion. The results suggested that a minimum of $T = 60$ is required for an acceptable estimate for the mean of the time-varying slope and a $T = 120$ is required for an acceptable estimate for the variance of time-varying slope. On top of that, a minimum of $N = 50$ seems to be sufficient for the estimation of the mean of the between-individual random intercept. However, due to the potential conflation of measurement error and the variance of random intercept, I am unable to provide an evidence-based suggestion on the sample size.

Nevertheless, the results seem to suggest that the modelling choice of estimating the random intercept can counter the effect of measurement unreliability but this choice would hinder a meaningful interpretation of the random intercept. The results on the random slope at the between-individual level also seem to indicate that an unusually large point-estimate of the variance parameter may be taken as an indication that the parameter is an over-specification in the model, which could be removed from the model and proceed with a re-estimation of the simpler model.

Chapter 6

General Discussion and Conclusion

This dissertation focused on three aspects of the intensive longitudinal methodology (ILM): the design, measurement, and analysis of intensive longitudinal data (ILD). Specifically, I examined selected statistical approaches in evaluating invariance in measurement and mediation with the presence of designed planned-missing data in the context of intensive longitudinal method (ILM).

The use of ILM in research studies has enjoyed an exponential growth in the last few decades (Hamaker & Wichers, 2017). A typical intensive longitudinal research takes about 1 to 2 weeks, with 2 to 12 measurement occasions per day. The frequent measurement required from the individuals inadvertently had been reported to caused burden and fatigue and researchers have suggested to use shorter measurement during each occasion (Scollon et al., 2009). Even though a single-item measurement would greatly reduce response burden, the reliability of the measurement could be affected. Therefore, instead of using single-item measurement, which is a common practice in ILM, I argued for the incorporation of planned-missing data design in the collection of ILM, particularly on the use of the three-form design, which has been commonly used in other fields of psychological research (Graham et al., 2006), based on the original multi-item measurement.

6.1 Summary of Studies

Measurement invariance is routinely tested in longitudinal panel data; however, the topic of measurement invariance has yet been widely explored in ILM. I believe this is likely due to the typical use single-item measurement in ILM, and also due to the statistical limitation of the longitudinal confirmatory factor analysis (CFA) framework in testing intensive longitudinal measurement invariance.

Study 1 reported in chapter 3 compared the Alignment method (Asparouhov & Muthén, 2014) and the cross-classified (time-varying effect) factor model as alternatives to the longitudinal CFA method to establish longitudinal measurement invariance through the detection of non-invariant measurement model intercept and factor loading parameters. In particular, the effect of sample size, length of measurement occasion, factor correlation, and the presence of missing data on the accuracy of the two methods in identifying the invariant and non-invariant measurement model parameters were investigated.

Collins (2006) argued that a good integration of theoretical model, temporal design, and statistical model are essential for effective answering of longitudinal research questions. Particularly, the statistical model must be able to correctly characterise the change process according to the theoretical model. This is especially challenging for the ILM because of the potential complex relationship between variables (e.g., autoregressive relationships and time-varying or time-invariant trends) that could occur. Recently, Asparouhov et al. (2018) introduced the dynamic structural equation modelling (DSEM) framework as a general modelling framework for the ILD. Given the novelty of the framework, only two papers on the evaluation of the framework had been published, albeit using relatively simple models (in terms of number of parameters; Asparouhov et al., 2018; Schultzberg & Muthén, 2018).

Once longitudinal measurement invariance has been established, the modelling of longitudinal differences and change can be proceeded (Meredith, 1964). Study 2 reported in chapter 4 evaluated the estimation of the structural parameters between latent variables in the 1-1-1 and 2-1-1 autoregressive multilevel fixed effect mediation mod-

els. Mediation model was chosen as the model of choice in the study for its regular use in the field of psychology. Similar to Study 1, the effect of sample size, length of measurement occasions, effect size, and the presence of missing data on the quality of parameter estimates (bias, coverage, and rejection) in the DSEM framework were examined.

The models tested in Study 2 are only appropriate for a theoretical model which specifies that associations between variables do not change over time (i.e., time-invariant). To test for time-varying associations between variables, the cross-classified model in the DSEM framework may be used. Implementation of the cross-classified model as a time-varying effect model (TVEM) is fairly straightforward using data with observations on the within-level that is nested under the crossed between-level units of individual and time. The time-varying effect in DSEM is modelled as a random effect at the between-time level similar to random effects at the between-individual level in regular multilevel regression or structural equation model.

Study 3 reported in chapter 5 investigated the estimation of the mean and variance of random intercepts and intercepts at both the between-time and between-individual levels. Similar to Study 2, the effect of sample size, length of measurement occasion, effect size, and the presence of missing data on the quality of parameter estimates (bias, coverage, and rejection) in the DSEM framework were examined. In addition to these factors, study 3 also evaluated the effect of measurement reliability on the quality of the estimates. Reliability was considered in this study because time-varying effect involving lagged latent variables cannot be modelled in the DSEM cross-classified model, therefore losing the ability to partial out the measurement error from the variables. Instead of structural relationship between latent variables such as those in study 2, the structural relationship between observed variables were modelled in study 3.

6.1.1 Key Results

The results from the studies illustrated the feasibility of using a three-form design as a method to introduce planned-missing data in ILD. This is based on the evidence

that the accuracy and the quality of the parameter estimate may be comparable between the complete-data conditions and the conditions with missing-data (even up to 40% missing-ness). However, the feasibility was primarily dependent on the method that the missing data was handled in the analysis procedure. For an instance, study 1 and study 2, which used latent measurement model to model the observed items, showed close to none to a manageable negative impact of the presence of missing data on the estimates; however, study 3, which used an observed composite score for the items via mean-replacement of missing data, showed a huge impact of missing data on the estimates. The negative impact was severe even when the measurements were highly reliable (e.g., $\omega = 0.80$).

Even though the results indicated that the presence of missing data would result in slightly larger bias and wider highest density interval (HDI) of the estimates, this bias could easily be mitigated by increasing the sample size. On the other hand, the impact of sample size and measurement occasions were dependent on the level of the model. For example, I did not observe difference in the estimates between levels of different measurement occasions in study 1 and 2; however, there was an effect of measurement occasions in the parameter at the between-time level (level 2) in study 3; Similarly, I only see a large impact of sample size at the between-individual level (level 2) in study 2 and study 3. These findings suggested that sample size and measurement occasion would only impact the parameters in the level in which the "information" was used (i.e., sample size for between-individual level parameters; measurement occasion for between-time level parameters). Moreover, the impact of the sample size and measurement occasions may differ, depending on the type of parameters (e.g., mean, variance). The mean parameter require smaller sample size or measurement occasion to reach an acceptable quality than a variance parameter. This is evidence in the mean and variance parameter of the random effects in study 3.

In testing mediation effect with ILD, the recovery of the parameter estimates may depend on the "location" of the variables associated to the parameter (i.e., relationship between predictor and the mediator, between mediator and the outcome, and between

the predictor and the outcome) as shown in study 2. The results implied a "trickle down" effect in that the lack of estimation precision in the preceding part of the causal relationship would be carried forward to the latter part of the causal relationship.

Lastly, the effect size did not affect the relative bias of the estimates. However, a parameter with larger effect size is more easily detected (i.e., more frequent rejection in testing the null value of 0 than a parameter with a small effect size), given that the relative bias was close to 0. This observation of effect size is consistent with the conventional knowledge of the null hypothesis significant testing framework.

6.2 Recommendations for Applied Researchers

I acknowledge that it may not be meaningful to provide specific guideline on sample size and measurement occasions requirements that is applicable to all ILD analyses. Based on the findings from the three simulation studies, the requirements may very much vary depending on the parameter of interest and the model under consideration. This conclusion is in-line with Schultzberg and Muthén (2018).

In the current dissertation, I simulated the planned-missing data as a three-form design that introduced up to 40% missing data (i.e., selectively removed up to 2 items from a 5-item scale or 40% of the total number of items for each measurement occasion). From a research design standpoint, I have shown that three-form design is a feasible method to be implemented in the intensive longitudinal data collection stage without a large impact on the parameter estimates when compared to a complete dataset, under the condition that the missing data can be properly handled in the model (e.g., the use of latent measurement model). Therefore, I do not recommend the use of the three-form design if a measurement model cannot be specified in the statistical model of interest, as illustrated in study 3 where limitation of the Mplus software on time-varying lagged latent variable prevented the use of a measurement model led the author to use composite-observed variable derived from available data (i.e., computing an observed score from available item at each item point; mean-replacement of miss-

ing data), thus leading to a negative impact on the parameter estimates compared to the complete-data condition.

To establish intensive longitudinal measurement invariance, the cross-classified factor model would be a better choice than the Alignment method. Even though the performance of both the factor model and the Alignment method were similar as observed from the study 1 simulation, the Alignment method inherently assumes independence of variables between time-points by treating the grouping-unit (i.e., time) as independent groups. The assumption of complete independent time-group is unlikely to hold true for longitudinal data. Therefore, I recommend the use of the cross-classified factor model, which is a more flexible method, to accommodate the correlations between factors and potentially the residuals similar to the longitudinal confirmatory factor analysis framework. Based on the results, at least a sample size of 200 (i.e., $N \geq 200$) is required for the analysis.

Based on the findings in study 2 on the estimation of structural parameters of a 1-1-1 or 2-1-1 mediation model, the sample size requirement for an acceptable quality of parameter estimate was at least 200 (i.e., $N \geq 200$) and the measurement occasion can be as small as 30 (i.e., $T \geq 30$). For a cross-classified model, the mean of a random slope at the between-time level requires at least 60 measurement occasions ($T \geq 60$) and the variance of the random slope at the between-time level requires at least 120 measurement occasions ($T \geq 120$). Instead of using non-informative prior in the Bayesian estimation, I strongly suggest the use of informative prior when possible. Using informative prior may result in a lower requirement of sample size and measurement occasion than the non-informative prior.

In summary, researchers will have to take the theoretical and statistical model into consideration when designing the research. Given the complexity of the ILD and DSEM, a one-size-fits-all recommendation is unrealistic. Beyond the recommendations provided in this section, I would further recommend applied researchers to conduct simulation study of their own to aid their research design and analysis plan.

6.3 Limitations and Future Directions

The design of intensive longitudinal study and analysis of intensive longitudinal data (ILD) have many aspects to consider beyond the scope of this dissertation. The study-specific limitations have been described in their respective chapters, the overarching limitations of the dissertation are enumerated in this section. In general, current simulation studies have a number of limitations in that the generalisation of the results beyond experiment conditions and models considered in the design is limited.

This limited generalisation is particularly true with regards to the simulation of missing data in the studies. The missing data simulated in the study was solely generated based on the three-form design in which the missing data were missing completely at random (MCAR). In actual research, the mechanism of missing data may not be as ideal and there could be a mix of MCAR stemming from the planned-missing data and possibly data that is missing not at random (MNAR) stemming from participant drop-out or refusal to respond. Future research may wish to investigate the handling of MNAR data in the dynamic structural equation model (DSEM) framework to further advance the methodology.

Moreover, all outcome variables in the studies (i.e., the items) were simulated as continuous variables which may not be a true reflection of real research data. Future research should investigate the generalisation of the results in this dissertation under conditions of order-categorical data especially polytomous data which may reflect items rated using a Likert scale more closely.

The studies in this dissertation simulated a relatively balanced interval-contingent design in which all individuals were measured at the same time-point for the same number of times. Recall that signal-contingent design, which participants respond at the point of receiving a prompt that would be sent at a random interval, is often used in intensive longitudinal research. The application of DSEM models on such design could be evaluated in the future in order to support the use of DSEM as a general framework for a variety of data collected from different intensive longitudinal research design.

Another limitation in the current evaluation of performance of DSEM is the use of

non-informative prior in Bayesian estimating of the parameters posterior distribution. I believe with the use of informative prior, the requirement of sample sizes and measurement occasions could be relaxed (i.e., smaller number sample sizes and occasions) than the one suggested in the previous section because an appropriate informative prior could better update the posterior along with the data likelihood (see Appendix A for the discussion on prior and posterior distribution). Therefore, more simulations can be done to evaluate the impact of the choice of informative prior on the resulting posterior distribution and the point-estimates and HDI of the parameters in DSEM.

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Appendix A

Overview of the Bayesian Method

The Bayesian statistics was developed about 150 years before the frequentist statistics (Kaplan & Depaoli, 2013) and was later introduced to the field of Psychology in 1960s but it did not receive traction for the next few decades (Kline, 2013) until recent years where researchers hail the Bayesian statistics as part of the New Statistics movement that shifts away from the emphasis on null hypothesis significance testing (e.g. Kruschke & Liddell, 2018).

Bayesian statistics fundamentally can be differentiated from the frequentist statistics on their interpretation of probability (Kaplan & Depaoli, 2013; Kruschke, 2014). The frequentist interprets probability as the frequency of events over (hypothetical) infinite number of observations; while the Bayesian treats probability as a subjective belief or uncertainty of events (Kaplan & Depaoli, 2013; Kruschke, 2014).

Apart from the differences in the concept of probability, the Frequentist views model parameters as unknown but fixed (i.e. a single value) at the population level; in contrast, the Bayesian statistics views parameters as unknown and random (i.e. a set of values) at the population level, that is, the parameters have a probability distribution that reflects the uncertainty about the true parameters value. The Bayes' Rule is a process of updating the uncertainty of the parameters (prior distribution; $p(\theta)$) by weighting it with the observed data (likelihood; $L(\theta|D)$), and resulting in an updated uncertainty of the parameters (posterior distribution; $p(\theta|D)$).

These distinctions are important to reach an intuitive understanding of the Bayes' Theorem which underlies Bayesian statistics inference.

A.1 Bayes' Rule

The Bayes' Rule (or Theorem) states in the context of data analysis following notations used in Kruschke (2015), that

$$p(\theta|D) = \frac{p(D|\theta) * p(\theta)}{p(D)} \quad (\text{A.1})$$

where θ refers to the parameter of a certain model, and D refers to the data used to fit the model.

In most data analysis application, the denominator ($p(D)$) which is the marginal probability of the data is considered a normalising factor to ensure the conditional probability (on the left-hand side of the equation) can be summed to one; therefore, there is no particular importance of this component in the estimation or inference (Kaplan & Depaoli, 2013), hence, A.1 is often written as

$$p(\theta|D) \propto p(D|\theta) * p(\theta) = L(\theta|D) * p(\theta) \quad (\text{A.2})$$

which expresses that the posterior (conditional) probability of parameters (θ) given the observed data ($p(\theta|D)$) is proportional to the conditional probability of the observed data given the parameters ($p(D|\theta)$) multiply by the prior (marginal) probability of the parameters ($p(\theta)$). $p(D|\theta)$ can also be written as the $L(\theta|D)$ likelihood of the parameters given the observed data. The posterior probability of parameters ($p(\theta|D)$) is the core of Bayesian statistical inference.

A.2 Prior Distribution

As introduced in the previous section on Bayes' Rule, uncertainty of a parameter is expressed as a probability distribution. A prior distribution of the parameters can be

understood as our current (or absence of) knowledge of the model parameters prior to collecting the data. Specification of a prior distribution in the estimation of the posterior distribution is a strength of the Bayesian statistics consistent with concept of knowledge accumulation of scientific progress where current knowledge (prior) is used to update our knowledge (posterior). It is commonly understood that the role of prior distribution on updating the posterior distribution gets smaller as the sample size increases (e.g., Muthén et al., 2017).

In the application of the Bayesian statistics, there are two types of prior that we can consider to employ: objective priors and subjective priors (Press, 2002).

A.2.1 Objective vs. Subjective Prior Distribution

Objective prior is also typically known as non-informative (or diffused) prior which is commonly characterised as a flat distribution to imply that all values in the parameter space are roughly equally probable so that the posterior distribution is minimally affected by the prior distribution. A common argument for the use of an non-informative prior is to allow the observed data to inform the posterior distribution without the influence of the subject prior knowledge. A related concept to the non-informative (objective) prior is the weakly informative prior that is commonly characterised as a uniform distribution that form numerical boundaries on the parameter space while retaining a minimal influence on the posterior distribution (Gelman et al., 2013). To contrast with the objective prior, subjective prior, or typically known as informative prior, is often used to represent the presence of prior knowledge about the parameter by a distribution that assigns different probability to each value in the parameter space (Gelman et al., 2013).

A.3 Point and Interval Estimates of Posterior Distribution

For inference, the posterior distribution of each parameter can be summarised by using a point estimate and the uncertainty of the parameter can be summarised using an interval. The point estimate of a distribution can be the typical central tendency indices such as the mean, median, or mode of the distribution (Gelman et al., 2013). Two common interval estimates are the credible interval and the highest density interval (HDI).

The credible interval contains parameter values that fall between an upper limit and a lower limit that create equal proportion in the upper tail and lower tail of the posterior distribution. The commonly used upper limit and lower limit of the credible interval would be the 2.5th and 97.5th percentiles, respectively, thus forming the 95% credible interval of the posterior distribution (e.g., Muthén et al., 2017). Similar to the 95% credible interval, the 95% highest density interval (HDI) also contains parameter values that fall between an upper limit and a lower limit, however to contrast it with the credible interval, the 95% HDI does not create an equal-tailed interval based on the percentiles of the posterior distribution. The parameter values that are within the 95% HDI are more likely than the values outside out the interval (Kruschke, 2014). When the posterior distribution is approximately unimodal and symmetrical, the credible interval and the HDI would be the similar; otherwise, the two intervals would produce different upper and lower limit for a specific interval.

A.4 Point Hypothesis Testing

Hypothesis testing approaches in Bayesian statistics can be roughly categorised into three inter-related categories (Makowski et al., 2019): Bayes factor, posterior-based indices, and Region of Practical Equivalence (ROPE)-based indices. Bayes factor can be used either for model selection or to test individual parameters in a model through an evaluation of relative evidence for one model over the other. Posterior-based indices

are simple indices based on properties of the posterior distribution such as the proportion of distribution that coincides with the sign of the parameter point estimate.

The ROPE-based indices are based on the concept of equivalence testing that focuses on effect sizes. ROPE defines a range of values that is equivalent to a null-value and the ROPE is often used with the highest density interval (HDI) as a means of hypothesis testing (e.g. Kruschke & Liddell, 2018; Makowski et al., 2019). The current dissertation used ROPE and HDI as the main approach of hypothesis testing, therefore this warrants elaboration.

A.4.1 ROPE and HDI

The Region of Practical Equivalence (ROPE) is defined as an interval of parameters values that are considered as practically equivalent to a null value for a particular application such as hypothesis testing. For instance, a possible ROPE interval for a correlation coefficient could be 0 ± 0.1 , representing the range of correlation coefficient of -0.1 and +0.1 is equivalent to a correlation coefficient of 0. If the highest density interval (HDI) of the posterior distribution excludes the ROPE, researcher could reject the targeted null value of the ROPE. On the other hand, if the ROPE completely contained the HDI, research may decide to accept the null value, which is not possible in the frequentist Null Hypothesis Significant Testing approach (NHST). Lastly, if ROPE and HDI overlaps partially, this may indicate that there is insufficient evidence to either reject or accept the null value (Kruschke, 2014).

The choice of the upper and lower limit of ROPE can be established either by practical expert opinion (Kruschke, 2014) or from established conventional effect size estimates (Kruschke, 2018). For example, a Cohen's d value of 0.2 is commonly interpreted as a small effect size, therefore a possible ROPE for the null value of Cohen's d could be 0 ± 0.1 (Kruschke, 2014). It is common to use 95% HDI with ROPE when there are large enough Markov Chain Monte Carlo sampling (see the next section), or else the HDI upper and lower limit may not be sufficiently stable nor precise (Kruschke, 2014). As an alternative, the 90% HDI or an even smaller HDI may be used.

A.5 Markov Chain Monte Carlo Methods and Convergence Diagnostics

While the Bayes' Rule can be solve analytically for simple models, it is more commonly to use a computational approach to approximate the posterior distribution in practice. A commonly used family of estimation algorithm is the Markov Chain Monte Carlo (MCMC) sampling method. The Metropolis-Hastings and Gibbs Samplings algorithms (and their variations) are two of the more commonly used MCMC algorithms. Generally an MCMC method contain three components: the Monte Carlo method refers to the repeated random sampling of values from a distribution in order to examine the properties of distribution itself; the Markov Chain refers to a specific property of the sampling process that the current k -th random sample is used to inform on the sampling of the new $(k+1)$ -th random sample and that the new sample only depends on the immediate previous samples and not any other samples; and a specific algorithm (e.g., Metropolis-Hasting, Gibbs sampling) to accept or reject the new random sampled values using information on the prior distribution and likelihood in forming the posterior distribution (van Ravenzwaaij et al., 2018).

For an example, the Gibbs Sampling MCMC, which is a common default algorithm in software such as BUGS, JAGS, and Mplus, is initiated with a starting value for each parameter in the model. In each of the following iterations, a new value for each parameter is sampled sequentially informed by the previous value of the parameters. The algorithm continues until a "chain" of values is formed. Due to the dependent on a starting value for the initiation of the algorithm, a wrong starting value (e.g., a value that is not within the bounds of the targeted posterior distribution) may affect the results. Therefore, more often than not, at least two independent chain for each parameters would be created by initiating the algorithm with two independent sets of starting value for each parameter rather than one in order to allow researcher to check for convergence of the chains to a similar set of values that form the posterior distribution. It is also a common practice to exclude a portion (usually half) of the chains to form the

final posterior distribution to avoid the influence of the starting values in each chain. The excluded portion is referred to as the burn-in samples (van de Schoot et al., 2014). For a more technical review of the MCMC methods, see Gelman et al. (2013) and Kruschke (2014).

As mentioned in the previous paragraph, it is important for the multiple chains to converge to the same set of values. To assess the convergence of the MCMC chains, a commonly used quantitative method is the potential scale reduction (PSR) factor. Convergence is statistically defined as a status when the between-chain variability is smaller relative to the within-chain variability (Muthén et al., 2017), which the PSR expresses as

$$PSR = \sqrt{\frac{\text{within-chain variability} + \text{between-chain variability}}{\text{within-chain variability}}} \quad (\text{A.3})$$

The PSR value that is close to 1 indicates that there is small between-chain variability (i.e. the "between-chain variability" component is close to 0) and therefore taken as evidence of convergence of the chains of a particular parameter. It is important for the chains for all parameters to converge in order to interpret the posterior distributions.

A.6 Missing Data

The MCMC method (e.g., Gibbs sampling) is able to estimate the posterior distribution of the parameters without modification under the assumption that the missing data are Missing at Random (Asparouhov et al., 2018; Lee, 2007).

Appendix B

Default Bayes Implementation in Mplus

B.1 Prior Distribution and MCMC

Given a regular structural equation model which contains both measurement and path models, the intercept and regression weights (i.e. factor loadings and structural paths) use a normally distributed prior distribution. The variance-covariance matrix of the measurement error and structural disturbances use the Inverse-Wishart or the Inverse-Gamma prior distribution depending on the algorithm. Mplus by default uses the blocked-Gibbs sampling MCMC algorithm to construct the approximated posterior distributions, while the Metropolis-Hasting algorithm and other alternatives are also available (controlled using the `ALGORITHM` option in the `ANALYSIS` command). See (Asparouhov & Muthén, 2010) for the technical implementation of the Bayesian method.

B.2 Convergence Diagnostics

The potential scale reduction(PSR) factor (also referred to as the Gelman-Rubin statistic) is used primarily to indicate convergence of the MCMC chains. The chains are thought to have converged if PSR for all parameters are smaller than $1 + \epsilon$, where

$\varepsilon = f * c$ which is dependent on the model. c is the convergence criterion (set as 0.05 default; controlled using the `BCONVERGENCE` option in the `ANALYSIS` command). f is computed as a function of the number of parameters (p) where

$$f = \text{NORMINV}(0.95^{1/p}, 0, 1) / 1.64485362695147.$$

More specifically, the PSR for all parameter were computed for every 100th iterations using the second half of the chains (i.e. the first half is discarded as burn-in). A minimum and maximum number of iterations or a fixed number of iterations for each chain can also be specified by using the `BITERATIONS` for the former or the `FBITERATIONS` under the `ANALYSIS` command. If a minimum and maximum iteration numbers are specified, the MCMC will terminate only after the minimum number of iterations and with the chains having a reasonable PSR. For example, if a minimum of 2000 iterations was specified, mplus will then evaluate the PSR to determine convergence using the last 1000 iterations from each chain. If convergence has not been reached, another 100 iterations will be done and the PSR evaluated using the last 50% of the total iterations of 2100 iterations from each chain, so on and so forth.

If the PSR for all parameters are smaller than the convergence criteria, say at the 5000th iteration (where the PSR is evaluated using the last 50% of the 5000 iterations for each chain, i.e. the last 2500 iterations), the posterior distribution of the parameters will be constructed using the last 2500 iterations for each chain (post burn-in). In general, assuming two chains, if n iterations has been done on each chain, the total number of iterations will be $2 * n$ for each parameter. Mplus uses the first half of each chain as burn-in by default, therefore, the posterior distribution for each parameter will be based on a total of n iterations.

Appendix C

Study 1 Materials

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C.1 Data Generating Scripts

```
n <- c(50, 200, 350) # sample size
j <- 5 # item/occassion
t <- c(30, 60) # occasion
rhoF <- c(0, 0.35, 0.70) # factor corr
rhoR <- c(0, 0.40) # error corr
invar <- c(0, 1) # invariance condition (0 = no [aka non-invariance], 1 = yes)
replicate <- 500
init.seed <- 56789012

# get custom functions
source("AR.R")
source("mvAR.R")
source("missing.R")
```

```

# current working directory
setwd("../")
MainDir <- getwd()

# to save simulation seed information
simInfo <- NULL

for (nn in n){
  for (jj in j){
    for (tt in t){
      for (ff in rhoF){
        for (rr in rhoR){
          for (mm in invar){

            # save information on simulation condition
            Info <- c(nn, jj, tt, ff, rr, mm, init.seed)
            simInfo <- rbind(simInfo, Info)

            ## generate parameters
            # non-invariant parameters (to occur at last 30% of the time)
            tau0 <- matrix(c(rep(0, jj*(tt-ceiling(tt*0.3))),
                           rep(c(0, 0, 0, 0, 0.5), tt*0.3/3),
                           rep(c(0, 0, 0, -0.5, 0), tt*0.3/3),
                           rep(c(0, 0, 0.5, 0, 0), tt*0.3/3)), nrow = tt, ncol= jj, byrow = T)
            lam0 <- matrix(c(rep(1, jj*(tt-ceiling(tt*0.3))),
                           rep(c(1, 1, 1.4, 1, 1), tt*0.3/3),
                           rep(c(1, 1, 1, 1, 0.5), tt*0.3/3),
                           rep(c(1, 1, 1, 0.3, 1), tt*0.3/3)), nrow = tt, ncol= jj, byrow = T)

            # invariant parameters
            tau1 <- matrix(rep(rep(0, jj), tt), nrow = tt, ncol = jj, byrow = T)
            lam1 <- matrix(rep(rep(1, jj), tt), nrow = tt, ncol = jj, byrow = T)

            # select parameters to use depending on condition
            if (mm == 0){
              tau <- tau0
              lam <- lam0
            }
          }
        }
      }
    }
  }
}

```

```

} else if (mm == 1){
  tau <- tau1
  lam <- lam1
}

# create planned missing pattern
forms <- matrix(c(1, 1, 1, 1, 0,
                 1, 1, 0, 1, 1,
                 1, 1, 1, 0, 1), nrow = 3, byrow = T)
varPat <- missing(forms, times = tt, N = nn, type = "vary")
conPat <- missing(forms, times = tt, N = nn, type = "constant")

# create sub-folders to save datasets under the DataAndOutput folder
DataDir <- file.path(MainDir, "DataAndOutput",
                    paste0("N", nn,
                           "J", jj,
                           "T", tt,
                           "F", ff*10,
                           "R", rr*10,
                           "IV", mm))
dir.create(DataDir); setwd(DataDir);

for (rep in 1:replicate){

  # generate factor scores
  set.seed(init.seed)
  eta <- MASS::mvrnorm(n = nn,
                      Sigma = AR(times = tt, rho = ff, sigma = 1),
                      mu = rep(0, tt),
                      empirical = F)

  # generate residual
  set.seed(init.seed)
  errvar <- MASS::mvrnorm(n = nn,
                          Sigma = mvAR(items = jj, times = tt, rho = rr, sigma = 1),
                          mu = rep(0, tt*jj),
                          empirical = F)

```

```

# generate observed data
data <- matrix(NA, nrow = nn, ncol = tt*jj)

k <- 0 # preset to loop through residual
for (qq in 1:tt){
  a <- 1 + k
  b <- jj + k

  [, a:b] <- matrix(rep(tau[qq, ], nn), ncol = jj, byrow = T) + matrix(eta[, qq], ncol = 1)
  %*% matrix(lam[qq, ], nrow = 1) + errvar[, a:b]

  k <- k + jj
}

# save data in wide format #####
wide_data_full <- cbind(seq(1:nn), data, eta)
write.table(wide_data_full, paste0('wide_data_full', rep, '.csv'), sep = ",", row.names = F,
  col.names = F)

# save data in long format
wide_data <- data.frame(wide_data_full)[, 1:(tt*jj + 1)]
varnames <- NULL
for (ss in 1:tt){
  varnames[[ss]] <- paste("Y", 1:jj, "_", as.character(ss), sep = "") # results in Y[item]_[
  time]
}
names(wide_data) <- c("ID", unlist(varnames))
long_data <- reshape(wide_data, varying = dput(names(wide_data)[-1], file = 'tmpt.txt'),
  idvar = "ID", direction = "long", sep = "_")
write.table(long_data, paste0('long_data_full', rep, '.csv'), sep = ",", row.names = F, col.
  names = F)

# create planned missing data (varying form administration) #####
wide_data_var <- data.frame(cbind(seq(1:nn), data * varPat))
write.table(wide_data_var, paste0('wide_data_var', rep, '.csv'), sep = ",", row.names = F,
  col.names = F)

names(wide_data_var) <- c("ID", unlist(varnames))

```



```

times <- 1:times
H <- abs(outer(times, times, "-"))
V <- sigma * rho^H
p <- nrow(V)
V[cbind(1:p, 1:p)] <- V[cbind(1:p, 1:p)] * sigma
V
}

```

C.1.2 Custom R Function: *mvAR()*

```

mvAR <- function(items = items, times = times, rho = rho, sigma = sigma){

  # create AR rho param in the form of blocks
  b1 <- sigma*diag(items)
  for (ii in 2:times){
    block <- paste0("b", ii)
    assign(block, b1*rho^(ii-1))
  }

  # compute block index for large matrix (based on the AR(1) function by Rizopoulos)
  t <- 1:times
  index <- abs(outer(t, t, "-")) + 1

  # create a list that contains matrices as objects
  K <- rep(list(matrix(NA, nrow = items, ncol = items)), times*times)

  for (ii in 1:times){
    K[which(index == ii)] <- rep(list(get(paste0("b", ii))), length(which(index == ii)))
  }

  # convert list to matrix
  mat <- NULL
  ctr <- 0

  for (ii in 1:times){
    mat <- cbind(mat, do.call(rbind, K[(1 + ctr):(times + ctr)]))
    ctr <- ctr + times
  }
}

```

```
}  
  mat  
}
```

C.1.3 Custom R Function: *missing()*

```
missing <- function(forms = forms, times = times, N = N, type = "vary"){  
  if (type == "vary"){  
    # create array for varying forms across {times} occasions  
    v1 <- rep(c(forms[1, ],  
               forms[2, ],  
               forms[3, ]), ceiling(times/3)) [1:(times*dim(forms)[2])]   
  
    v2 <- rep(c(forms[2, ],  
               forms[3, ],  
               forms[1, ]), ceiling(times/3)) [1:(times*dim(forms)[2])]   
  
    v3 <- rep(c(forms[3, ],  
               forms[1, ],  
               forms[2, ]), ceiling(times/3)) [1:(times*dim(forms)[2])]   
  
    mat <- matrix(c(rep(v1, ceiling(N/3)),  
                  rep(v2, ceiling(N/3)),  
                  rep(v3, ceiling(N/3))), byrow = T, ncol = length(v1)) [1:N, ]  
  
  } else if (type == "constant"){  
    # create array for constant forms across {times} occasions  
    c1 <- rep(forms[1, ], times)  
    c2 <- rep(forms[2, ], times)  
    c3 <- rep(forms[3, ], times)  
  
    mat <- matrix(c(rep(c1, ceiling(N/3)),
```

```

        rep(c2, ceiling(N/3)),
        rep(c3, ceiling(N/3))), byrow = T, ncol = length(c1))[1:N, ]
} else stop("no such type. Enter either 'vary' or 'constant'")
mat
}

```

C.2 Mplus Input File For Model Fitting

C.2.1 Alignment with Bayesian Method

```

TITLE: Alignment simulation;

DATA:
  FILE IS long_data.csv;

VARIABLE:
  NAMES ARE ID time Y1-Y5;
  USEVAR ARE Y1-Y5;
  CLASSES ARE c(30); ! T = 30; Change to 60 if T = 60
  KNOWNCLASS IS c(time);
  MISSING ARE Y1-Y5 (0);

ANALYSIS:
  TYPE IS MIXTURE;
  ESTIMATOR IS BAYES;
  BITER IS 12000(8000); ! at least 8k, but max 12k
  ALIGNMENT IS FREE;
  PROCESS IS 2;

MODEL:
  %overall%
  F By Y1-Y5;

```

```
OUTPUT:
  ALIGN TECH8 CINT(HPD);
```

```
PLOT:
  TYPE IS PLOT2;
```

C.2.2 Cross-Classified Method

```
TITLE: Alignment simulation;
```

```
DATA:
  FILE IS long_data.csv;
```

```
VARIABLE:
  NAMES ARE id time Y1-Y5;
  USEVAR ARE Y1-Y5;
  MISSING ARE Y1-Y5 (0);
  CLUSTER IS id time; ! level2b = id, level2a = time (time within id)
```

```
ANALYSIS:
  TYPE IS CROSSCLASSIFIED RANDOM;
  ESTIMATOR IS BAYES;
  BITER IS 6000 (4500);
  PROCESS IS 2;
```

```
MODEL:
  %WITHIN%
  L1-L5 | F BY Y1-Y5;
  [F@0]; F@1;

  %BETWEEN time%
  [L1-L5]; ! random effect of slope
  L1-L5; ! fixed effect of slope
  Y1-Y5;
  [Y1-Y5];
```

```
%BETWEEN id%  
[F@0]; F*;  
[L1-L5@0]; L1-L5@0;  
Y1-Y5;  
[Y1-Y5@0];
```

```
OUTPUT:  
TECH8 CINT (HPD);
```

```
PLOT:  
TYPE IS PLOT2;
```

```
SAVEDATA:  
FILE IS fscores.csv;  
FACTOR IS L1-L5 Y1-Y5;  
SAVE IS FSCORES(100);
```

C.3 Ad-Hoc Comparison Algorithm

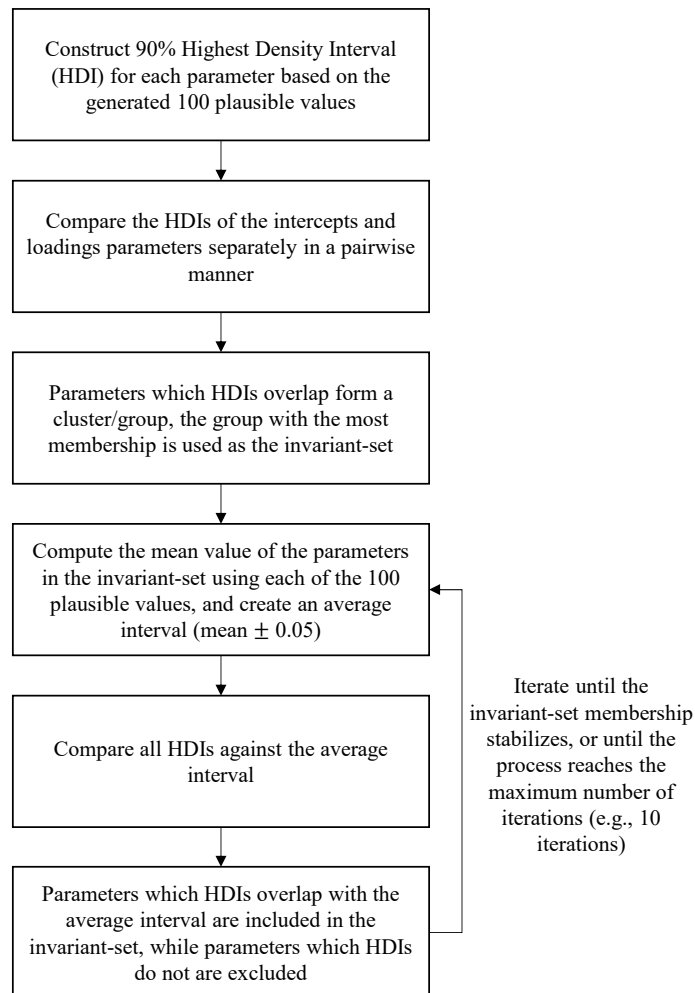


Figure C.3.1: Diagrammatic Implementation of Algorithm

```

# load all the packages that are required
packages <- c("dplyr", "HDInterval", "DescTools", "igraph")
if (length(setdiff(packages, rownames(installed.packages()))) > 0) {
  install.packages(setdiff(packages, rownames(installed.packages())))
}

library(dplyr)
library(HDInterval)
library(DescTools)
library(igraph)

# "alignment" (cross-classified approach)
aligncc <- function(fscores, time = 30){

  # rename variables
  names(fscores) <- c(paste("FW", c("Mean", "Median", "SD", "2.5", "97.5"), sep = "_"),
    paste("FTime", c("Mean", "Median", "SD", "2.5", "97.5"), sep = "_"),
    paste("L1_time", c(1:100, "Mean", "Median", "SD", "2.5", "97.5"), sep = "_"),
    paste("L2_time", c(1:100, "Mean", "Median", "SD", "2.5", "97.5"), sep = "_"),
    paste("L3_time", c(1:100, "Mean", "Median", "SD", "2.5", "97.5"), sep = "_"),
    paste("L4_time", c(1:100, "Mean", "Median", "SD", "2.5", "97.5"), sep = "_"),
    paste("L5_time", c(1:100, "Mean", "Median", "SD", "2.5", "97.5"), sep = "_"),
    paste("FIndi", c("Mean", "Median", "SD", "2.5", "97.5"), sep = "_"),
    paste("L1_indi", c(1:100, "Mean", "Median", "SD", "2.5", "97.5"), sep = "_"),
    paste("L2_indi", c(1:100, "Mean", "Median", "SD", "2.5", "97.5"), sep = "_"),
    paste("L3_indi", c(1:100, "Mean", "Median", "SD", "2.5", "97.5"), sep = "_"),
    paste("L4_indi", c(1:100, "Mean", "Median", "SD", "2.5", "97.5"), sep = "_"),
    paste("L5_indi", c(1:100, "Mean", "Median", "SD", "2.5", "97.5"), sep = "_"),
    paste("Y1_time", c(1:100, "Mean", "Median", "SD", "2.5", "97.5"), sep = "_"),
    paste("Y2_time", c(1:100, "Mean", "Median", "SD", "2.5", "97.5"), sep = "_"),
    paste("Y3_time", c(1:100, "Mean", "Median", "SD", "2.5", "97.5"), sep = "_"),
    paste("Y4_time", c(1:100, "Mean", "Median", "SD", "2.5", "97.5"), sep = "_"),
    paste("Y5_time", c(1:100, "Mean", "Median", "SD", "2.5", "97.5"), sep = "_"),
    paste("Y1_indi", c(1:100, "Mean", "Median", "SD", "2.5", "97.5"), sep = "_"),
    paste("Y2_indi", c(1:100, "Mean", "Median", "SD", "2.5", "97.5"), sep = "_"),
    paste("Y3_indi", c(1:100, "Mean", "Median", "SD", "2.5", "97.5"), sep = "_"),
    paste("Y4_indi", c(1:100, "Mean", "Median", "SD", "2.5", "97.5"), sep = "_"),
    paste("Y5_indi", c(1:100, "Mean", "Median", "SD", "2.5", "97.5"), sep = "_"),

```

```

      "indi", "time")

loading_list <- c("L1_time", "L2_time", "L3_time", "L4_time", "L5_time")
intercept_list <- c("Y1_time", "Y2_time", "Y3_time", "Y4_time", "Y5_time")

# intercept -----
intercept_results <- NULL
for (parameter in 1:length(intercept_list)){
  # obtain 90% credible interval
  param <- fscores %>%
    select(starts_with(intercept_list[parameter]),
           -ends_with("Mean"), -ends_with("Median"), -ends_with("SD"),
           -ends_with("2.5"), -ends_with("97.5")) %>%
    t()

  param_hdi <- hdi(param, credMass = 0.90) %>% t() %>% as.data.frame()

  # form initial cluster (find pairs of param that overlaps)
  pair_comp <- combn(seq(1, time), m = 2) #
  sets <- NULL
  for (ii in seq(1, ncol(pair_comp))){

    over <- param_hdi[pair_comp[, ii][1], ] %overlaps% param_hdi[pair_comp[, ii][2], ]

    if (isTRUE(over)){
      sets <- rbind(sets, pair_comp[, ii])
    }
  }

  m <- get.adjacency(graph.edgelist(as.matrix(sets), directed = FALSE))
  clus <- groups(components(graph_from_adjacency_matrix(m)))
  init_group <- clus[[which(unlist(lapply(clus, length)) == max(unlist(lapply(clus, length))))]]
  init_mean <- mean(colMeans(param[, init_group])) # obtain mean of the init clusters

  # check all HDI with init_mean
  old_group <- init_group
  group_mean <- init_mean
  new_group <- NULL

```

```

iter <- 1
while (isFALSE(identical(old_group, new_group))){

  # redefine old_group
  old_group <- new_group

  sets <- NULL
  for (ii in seq(1, 60)){
    over <- param_hdi[ii, ] %overlaps% c(group_mean - 0.05, group_mean + 0.05)
    if (isTRUE(over)){
      sets <- rbind(sets, ii)
    }
  }
  new_group <- as.integer(sets[, 1])
  group_mean <- mean(colMeans(param[, new_group]))

  # while controller max iter at 30
  iter <- iter + 1
  if (iter > 30){
    break
  }
}
invar_group <- new_group

# label the non-invar parameters as a negative value
full_group <- seq(1, time)
invar <- setdiff(full_group, invar_group)
full_group[invar] <- -full_group[invar]

# rbind parameters
intercept_results <- rbind(intercept_results, cbind(parameter, t(full_group)))
}

# loadings -----
loadings_results <- NULL
for (parameter in 1:length(loading_list)){
  # obtain 90% credible interval

```

```

param <- fscores %>%
  select(starts_with(loading_list[parameter]),
         -ends_with("Mean"), -ends_with("Median"), -ends_with("SD"),
         -ends_with("2.5"), -ends_with("97.5")) %>%
  t()

param_hdi <- hdi(param, credMass = 0.90) %>% t() %>% as.data.frame()

# form initial cluster (find pairs of param that overlaps)
pair_comp <- combn(seq(1, time), m = 2) # t = 30
sets <- NULL
for (ii in seq(1, ncol(pair_comp))) {

  over <- param_hdi[pair_comp[, ii][1], ] %overlaps% param_hdi[pair_comp[, ii][2], ]

  if (isTRUE(over)) {
    sets <- rbind(sets, pair_comp[, ii])
  }
}

m <- get.adjacency(graph.edgelist(as.matrix(sets), directed = FALSE))
clus <- groups(components(graph_from_adjacency_matrix(m)))
init_group <- clus[[which(unlist(lapply(clus, length)) == max(unlist(lapply(clus, length))))]]
init_mean <- mean(colMeans(param[, init_group])) # obtain mean of the init clusters

# check all HDI with init_mean
old_group <- init_group
group_mean <- init_mean
new_group <- NULL

iter <- 1
while (isFALSE(identical(old_group, new_group))) {

  # redefine old_group
  old_group <- new_group

  sets <- NULL
  for (ii in seq(1, time)) {

```

```

    over <- param_hdi[ii, ] %overlaps% c(group_mean - 0.05, group_mean + 0.05)
    if (isTRUE(over)){
      sets <- rbind(sets, ii)
    }
  }
  new_group <- as.integer(sets[, 1])
  group_mean <- mean(colMeans(param[, new_group]))

  # while controller max iter at 30
  iter <- iter + 1
  if (iter > 30){
    break
  }
}
invar_group <- new_group

# label the non-invar parameters as a negative value
full_group <- seq(1, time)
invar <- setdiff(full_group, invar_group)
full_group[invar] <- -full_group[invar]

# rbind parameters
loadings_results <- rbind(loadings_results, cbind(parameter, t(full_group)))
}

list("thres" = intercept_results,
     "load" = loadings_results)
}

```

Appendix D

Study 2 Materials

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D.1 Data Generating Scripts

D.1.1 1-1-1 Mediation Model

```
TITLE:
  1-1-1 mediation (no random lag);

MONTECARLO:
  NAMES ARE x1 x2 x3 x4 x5
            m1 m2 m3 m4 m5
            y1 y2 y3 y4 y5;
  NCSIZES = 1;
  SEED = 2840;
```

```
CSIZES = 350(60); ! N size (T size)
NOBS = 21000; !N size * T size
NREP = 500;
REPSAVE = ALL;
SAVE = data*.csv;
```

ANALYSIS:

```
TYPE IS TWOLEVEL;
ESTIMATOR IS BAYES;
FBITER IS 1;
ALGORITHM IS GIBBS;
PROCESS IS 2;
```

MODEL POPULATION:

%WITHIN%

```
! factor loadings
FXW BY x1*0.70 x2-x5*0.70 (&1);
FMW BY m1*0.70 m2-m5*0.70 (&1);
FYW BY y1*0.70 y2-y5*0.70 (&1);
```

```
! indicator error variance
x1-x5*.51;
m1-m5*.51;
y1-y5*.51;
```

```
! autoregression
FXW ON FXW&1*0.20;
FMW ON FMW&1*0.20;
FYW ON FYW&1*0.20;
```

```
! mediations (small effect condition)
FYW ON FMW&1*0.30;
FYW ON FXW&1*0.30;
FMW ON FXW&1*0.30;
```

```
! disturbance variance (small effect condition)
FXW*0.96; FMW*0.87; FYW*0.78;
```

```

! mediations (large effect condition)
!FYW ON FMW&1*0.60;
!FYW ON FXW&1*0.60;
!FMW ON FXW&1*0.60;

! disturbance variance (large effect condition)
!FXW*0.96; FMW*0.60; FYW*0.24;

```

```
%BETWEEN%
```

```

! factor loadings
FXB BY x1*0.459 x2-x5*0.459;
FMB BY m1*0.459 m2-m5*0.459;
FYB BY y1*0.459 y2-y5*0.459;

```

```

! indicator error variances
x1-x5*0.2193;
m1-m5*0.2193;
y1-y5*0.2193;

```

```

! mediations (small effect condition)
FYB ON FXB*0.30;
FYB ON FMB*0.30;
FMB ON FXB*0.30;

```

```

! factor/ disturbance variance (small effect condition)
FXB*1; FMB*0.91; FYB*0.82;

```

```

! mediation (large effect condition)
!FYB ON FXB*0.60;
!FYB ON FMB*0.60;
!FMB ON FXB*0.60;

```

```

! factor/ disturbance variance (large effect condition)
!FXB*1; FMB*0.64; FYB*0.28;

```

```
MODEL:
```

```
%WITHIN%
```

```
FXW BY x1@1 x2-x5 (&1);
```

```
FMW BY m1@1 m2-m5 (&1);
FYW BY y1@1 y2-y5 (&1);
```

```
x1-x5;
m1-m5;
y1-y5;
```

```
FXW; FMW; FYW;
```

```
FXW ON FXW&1;
FMW ON FMW&1;
FYW ON FYW&1;
```

```
FYW ON FMW&1;
FYW ON FXW&1;
FMW ON FXW&1;
```

```
%BETWEEN%
```

```
FXB BY x1@1 x2-x5;
FMB BY m1@1 m2-m5;
FYB BY y1@1 y2-y5;
```

```
FXB; FMB; FYB;
```

```
x1-x5;
m1-m5;
y1-y5;
```

```
FYB ON FXB;
FYB ON FMB;
FMB ON FXB;
```

```
OUTPUT: TECH8 TECH9;
```

D.1.2 2-1-1 Mediation Model

```
TITLE:
```

2-1-1 mediation (no random lag);

MONTECARLO:

```
NAMES ARE x
          m1 m2 m3 m4 m5
          y1 y2 y3 y4 y5;
BETWEEN = x;
CUTPOINTS = x(0);
NCSIZES = 1;
SEED = 2746;
CSIZES = 350(60); ! N size (T size) [change according to N and T]
NOBS = 21000; !N size * T size
NREP = 500;
REPSAVE = ALL;
SAVE = data*.csv;
```

ANALYSIS:

```
TYPE IS TWOLEVEL;
ESTIMATOR IS BAYES;
FBITER IS 1;
ALGORITHM IS GIBBS;
PROCESS IS 2;
```

MODEL POPULATION:

```
%WITHIN%
! factor loadings
FMW BY m1*0.70 m2-m5*0.70 (&1);
FYW BY y1*0.70 y2-y5*0.70 (&1);

! indicator error variance
m1-m5*.51;
y1-y5*.51;

! autoregression
FMW ON FMW&1*0.20;
FYW ON FYW&1*0.20;

! path model (within-level) [small effect condition]
```

```

FYW ON FMW&1*0.30;

! disturbance variance [small effect condition]
FMW*0.96; FYW*0.87;

! path model (within-level)[large effect condition]
!FYW ON FMW&1*0.60;

! disturbance variance [large effect condition]
!FMW*0.96; FYW*0.60;

%BETWEEN%
! factor loadings
FMB BY m1*0.459 m2-m5*0.459;
FYB BY y1*0.459 y2-y5*0.459;

! indicator error variances
m1-m5*0.2193;
y1-y5*0.2193;

! mediation [small effect condition]
FYB ON x*0.30;
FYB ON FMB*0.30;
FMB ON x*0.30;

! factor/ disturbance variance [small effect condition]
FMB*0.91; FYB*0.82; x@1; [x@0]

! mediation [large effect condition]
!FYB ON x*0.60;
!FYB ON FMB*0.60;
!FMB ON x*0.60;

! factor/ disturbance variance [large effect condition]
!FMB*0.64; FYB*0.28; x@1; [x@0]

```

```

MODEL:
  %WITHIN%

```

```
FMW BY m1@1 m2-m5 (&1);
FYW BY y1@1 y2-y5 (&1);
```

```
m1-m5;
y1-y5;
```

```
FMW; FYW;
```

```
FMW ON FMW&1;
FYW ON FYW&1;
```

```
FYW ON FMW&1;
```

```
%BETWEEN%
```

```
FMB BY m1@1 m2-m5;
FYB BY y1@1 y2-y5;
```

```
FMB; FYB;
```

```
m1-m5;
y1-y5;
```

```
FYB ON x;
FYB ON FMB;
FMB ON x;
```

```
OUTPUT: TECH8 TECH9;
```

D.2 Mplus Input File For Model Fitting

D.2.1 1-1-1 Mediation Model

```
TITLE:
  1-1-1 mediation (no random lag);
```

```

DATA:
  FILE IS data.csv;

VARIABLE:
  NAMES ARE x1-x5 m1-m5 y1-y5 ID;
  USEVARIABLES ARE x1-y5;
  CLUSTER IS ID;

ANALYSIS:
  TYPE IS TWOLEVEL;
  ESTIMATOR IS BAYES;
  BITER IS 10000(6000); ! change to 12000(8000) for missing conditions
  PROCESS IS 2;

MODEL:
  %WITHIN%
    ! factor loadings
    FXW BY x1@1 x2-x5 (&1);
    FMW BY m1@1 m2-m5 (&1);
    FYW BY y1@1 y2-y5 (&1);

    ! indicator error variance
    x1-x5;
    m1-m5;
    y1-y5;

    ! autoregression
    FXW ON FXW&1;
    FMW ON FMW&1;
    FYW ON FYW&1;

    ! mediations
    FYW ON FMW&1 (bw);
    FYW ON FXW&1;
    FMW ON FXW&1 (aw);

    ! disturbance variance

```

```
FXW; FMW; FYW;

%BETWEEN%
! factor loadings
FXB BY x1@1 x2-x5;
FMB BY m1@1 m2-m5;
FYB BY y1@1 y2-y5;

! indicator error variances
x1-x5;
m1-m5;
y1-y5;

! mediation
FYB ON FXB;
FYB ON FMB (bb);
FMB ON FXB (ab);

! factor/ disturbance variance
FXB; FMB; FYB;
```

```
OUTPUT:
TECH8 STAND CINT(HPD);
```

```
PLOT:
TYPE IS PLOT2;
```

D.2.2 2-1-1 Mediation Model

```
TITLE:
2-1-1 mediation (no random lag);
```

```
DATA:
FILE IS data.csv;
```

```
VARIABLE:
NAMES ARE m1-m5 y1-y5 x ID;
```

```
USEVARIABLES ARE m1-x;  
BETWEEN IS x;  
CLUSTER IS ID;
```

ANALYSIS:

```
TYPE IS TWOLEVEL;  
ESTIMATOR IS BAYES;  
BITER IS 10000(6000); ! change to 12000(8000) for missing  
PROCESS IS 2;
```

MODEL:

%WITHIN%

```
FMW BY m1@1 m2-m5 (&1);  
FYW BY y1@1 y2-y5 (&1);
```

```
m1-m5;  
y1-y5;
```

```
FMW; FYW;
```

```
FMW ON FMW&1;  
FYW ON FYW&1;
```

```
FYW ON FMW&1;
```

%BETWEEN%

```
FMB BY m1@1 m2-m5;  
FYB BY y1@1 y2-y5;
```

```
FMB; FYB;
```

```
m1-m5;  
y1-y5;
```

```
FYB ON x;  
FYB ON FMB (bb);  
FMB ON x (ab);
```

OUTPUT:
TECH8 STAND CINT (HPD);

PLOT:
TYPE IS PLOT2;

D.3 1-1-1 Model and 2-1-1 Model Over-specified Parameters

D.3.1 1-1-1 Mediation Model

Table D.1: 1-1-1 Mediation Model Level-1 Disturbance Correlation $\sigma = 0$

T	ES	PMD	N					
			25	50	100	200	350	
σ_{XM}								
30	0.3	0%	0.006 (0.048)	0.002 (0.035)	0.001 (0.023)	0.001 (0.016)	0.000 (0.012)	
		20%	0.005 (0.050)	0.003 (0.036)	0.000 (0.025)	0.001 (0.016)	0.000 (0.013)	
		40%	0.004 (0.054)	0.004 (0.040)	-0.001 (0.028)	0.001 (0.018)	0.000 (0.014)	
	0.6	0%	0.015 (0.050)	0.004 (0.036)	0.000 (0.023)	0.000 (0.018)	-0.002 (0.014)	
		20%	0.013 (0.055)	0.003 (0.039)	-0.001 (0.025)	0.000 (0.019)	-0.001 (0.014)	
		40%	0.012 (0.060)	0.003 (0.042)	0.000 (0.028)	-0.001 (0.020)	-0.002 (0.016)	
	60	0.3	0%	0.003 (0.031)	0.001 (0.023)	-0.002 (0.016)	0.000 (0.011)	0.000 (0.009)
			20%	0.003 (0.032)	0.001 (0.025)	-0.001 (0.017)	0.000 (0.012)	0.000 (0.009)
			40%	0.002 (0.036)	0.002 (0.025)	-0.002 (0.019)	0.000 (0.013)	0.001 (0.010)
0.6		0%	0.003 (0.035)	0.000 (0.024)	0.000 (0.018)	0.001 (0.013)	0.000 (0.009)	
		20%	0.003 (0.038)	0.000 (0.026)	0.001 (0.019)	0.001 (0.013)	0.000 (0.010)	
		40%	0.002 (0.041)	0.002 (0.030)	0.000 (0.021)	0.001 (0.015)	0.000 (0.010)	
σ_{XY}								
30		0.3	0%	0.005 (0.046)	0.000 (0.033)	0.000 (0.024)	0.001 (0.017)	0.001 (0.012)
			20%	0.001 (0.050)	0.001 (0.036)	0.001 (0.026)	0.000 (0.018)	0.001 (0.012)
	40%		0.002 (0.052)	-0.002 (0.039)	0.003 (0.027)	-0.001 (0.019)	0.000 (0.014)	
	0.6	0%	0.006 (0.066)	-0.003 (0.046)	0.001 (0.032)	-0.001 (0.022)	0.001 (0.018)	
		20%	0.002 (0.071)	0.000 (0.050)	0.002 (0.035)	-0.001 (0.025)	0.001 (0.020)	
		40%	0.001 (0.082)	-0.005 (0.060)	0.004 (0.039)	-0.003 (0.027)	0.001 (0.021)	
	60	0.3	0%	-0.001 (0.033)	0.002 (0.022)	0.000 (0.016)	0.000 (0.011)	0.000 (0.009)
			20%	0.001 (0.035)	0.001 (0.024)	0.000 (0.017)	0.000 (0.012)	0.000 (0.010)
			40%	-0.001 (0.037)	0.002 (0.026)	-0.001 (0.019)	0.001 (0.013)	0.000 (0.010)
0.6		0%	0.000 (0.045)	0.001 (0.032)	-0.001 (0.021)	0.000 (0.016)	0.000 (0.012)	
		20%	0.006 (0.049)	0.001 (0.034)	-0.001 (0.023)	0.000 (0.018)	-0.001 (0.013)	
		40%	0.002 (0.054)	0.002 (0.039)	-0.001 (0.026)	0.000 (0.020)	0.000 (0.015)	
σ_{MY}								
30		0.3	0%	0.006 (0.048)	0.003 (0.032)	0.003 (0.024)	0.002 (0.017)	0.001 (0.013)
			20%	0.007 (0.052)	0.002 (0.035)	0.003 (0.025)	0.002 (0.018)	0.002 (0.014)
	40%		0.010 (0.055)	0.002 (0.038)	0.004 (0.028)	0.000 (0.019)	0.002 (0.015)	
	0.6	0%	0.001 (0.074)	-0.003 (0.048)	0.005 (0.037)	0.000 (0.025)	-0.001 (0.020)	
		20%	0.005 (0.080)	-0.004 (0.055)	0.004 (0.043)	-0.001 (0.028)	-0.001 (0.021)	
		40%	0.013 (0.096)	-0.006 (0.062)	0.005 (0.047)	0.000 (0.033)	-0.001 (0.027)	
	60	0.3	0%	0.000 (0.035)	-0.001 (0.024)	0.001 (0.017)	0.000 (0.011)	0.000 (0.009)
			20%	0.001 (0.036)	0.001 (0.026)	0.001 (0.017)	0.000 (0.012)	0.000 (0.010)
			40%	0.002 (0.040)	-0.001 (0.028)	0.000 (0.019)	0.001 (0.014)	0.001 (0.011)
0.6		0%	-0.002 (0.051)	0.000 (0.034)	-0.004 (0.026)	0.000 (0.018)	-0.001 (0.013)	
		20%	-0.003 (0.060)	-0.002 (0.039)	-0.005 (0.029)	-0.001 (0.021)	0.000 (0.014)	
		40%	-0.001 (0.072)	0.001 (0.044)	-0.006 (0.033)	0.002 (0.024)	-0.001 (0.017)	

Note: N = Sample Size; T = measurement occasions; ES = Effect Size, PMD = Planned-Missing Data Rate. See Figure 4.3.3 for the three parameters of interest σ_{XM} , σ_{XY} , and σ_{MY} . The values without the parenthesis represent the mean of the parameter averaged across successful replications and the values within the parenthesis represent the standard deviation of the parameter across successful replications.

Table D.2: 1-1-1 Mediation Model Level-2 Indicator Intercepts $\mu = 0$

T	ES	PMD	N					
			25	50	100	200	350	
μ_X								
30	0.3	0%	-0.006 (0.138)	-0.007 (0.093)	0.002 (0.069)	-0.002 (0.049)	0.002 (0.037)	
		20%	-0.006 (0.139)	-0.002 (0.094)	-0.001 (0.070)	-0.002 (0.050)	0.001 (0.038)	
		40%	-0.006 (0.144)	0.002 (0.099)	-0.002 (0.072)	-0.003 (0.051)	0.001 (0.038)	
	0.6	0%	0.002 (0.134)	0.005 (0.097)	0.000 (0.067)	-0.001 (0.047)	0.000 (0.037)	
		20%	0.008 (0.135)	0.001 (0.096)	-0.003 (0.067)	0.001 (0.047)	-0.001 (0.037)	
		40%	0.002 (0.138)	0.001 (0.101)	-0.007 (0.069)	-0.001 (0.048)	0.000 (0.038)	
	60	0.3	0%	-0.005 (0.131)	-0.001 (0.094)	-0.001 (0.067)	0.001 (0.048)	0.001 (0.037)
			20%	0.003 (0.129)	-0.002 (0.096)	0.000 (0.067)	-0.002 (0.048)	-0.002 (0.037)
			40%	-0.003 (0.136)	-0.003 (0.094)	-0.002 (0.068)	-0.001 (0.048)	0.000 (0.037)
0.6		0%	0.004 (0.131)	0.000 (0.096)	0.001 (0.066)	0.003 (0.047)	0.005 (0.035)	
		20%	0.007 (0.131)	0.000 (0.096)	0.004 (0.067)	0.000 (0.047)	0.002 (0.035)	
		40%	0.004 (0.136)	-0.001 (0.096)	0.003 (0.067)	0.002 (0.048)	0.004 (0.035)	
μ_M								
30		0.3	0%	0.001 (0.135)	-0.005 (0.094)	0.001 (0.067)	-0.004 (0.048)	0.000 (0.037)
			20%	-0.001 (0.135)	-0.006 (0.094)	0.002 (0.067)	-0.002 (0.049)	0.000 (0.037)
	40%		-0.001 (0.142)	-0.003 (0.098)	-0.001 (0.070)	-0.002 (0.050)	-0.002 (0.038)	
	0.6	0%	-0.005 (0.139)	0.005 (0.100)	0.000 (0.068)	-0.001 (0.047)	0.000 (0.037)	
		20%	0.000 (0.139)	0.003 (0.099)	-0.001 (0.069)	0.002 (0.047)	-0.001 (0.038)	
		40%	-0.010 (0.142)	0.003 (0.100)	-0.007 (0.071)	0.000 (0.049)	-0.002 (0.039)	
	60	0.3	0%	0.003 (0.130)	-0.002 (0.092)	0.001 (0.067)	0.001 (0.048)	0.001 (0.036)
			20%	0.001 (0.131)	-0.002 (0.091)	-0.003 (0.067)	0.000 (0.048)	0.000 (0.036)
			40%	0.003 (0.134)	0.001 (0.091)	0.001 (0.068)	0.001 (0.048)	0.000 (0.036)
0.6		0%	0.001 (0.129)	-0.002 (0.093)	-0.001 (0.069)	-0.001 (0.048)	0.005 (0.036)	
		20%	0.001 (0.128)	0.001 (0.093)	0.000 (0.069)	-0.003 (0.049)	0.003 (0.036)	
		40%	0.005 (0.132)	0.002 (0.093)	0.001 (0.070)	-0.001 (0.049)	0.004 (0.036)	
μ_Y								
30		0.3	0%	-0.003 (0.146)	-0.004 (0.098)	0.000 (0.071)	-0.002 (0.050)	0.005 (0.037)
			20%	-0.003 (0.148)	-0.007 (0.098)	-0.004 (0.071)	0.000 (0.050)	0.005 (0.037)
	40%		-0.001 (0.149)	0.000 (0.101)	-0.002 (0.072)	-0.003 (0.051)	0.003 (0.038)	
	0.6	0%	-0.005 (0.154)	0.003 (0.105)	0.003 (0.077)	-0.002 (0.053)	0.001 (0.042)	
		20%	0.002 (0.153)	0.000 (0.106)	-0.002 (0.078)	0.002 (0.054)	0.000 (0.042)	
		40%	-0.010 (0.158)	0.001 (0.108)	-0.007 (0.079)	-0.002 (0.055)	0.000 (0.042)	
	60	0.3	0%	-0.014 (0.133)	-0.005 (0.097)	-0.002 (0.072)	0.002 (0.046)	-0.001 (0.038)
			20%	0.000 (0.133)	-0.001 (0.096)	0.002 (0.071)	0.000 (0.046)	-0.002 (0.038)
			40%	-0.010 (0.136)	-0.009 (0.097)	0.002 (0.073)	0.002 (0.047)	-0.002 (0.038)
0.6		0%	-0.003 (0.141)	-0.004 (0.106)	-0.001 (0.075)	0.002 (0.054)	0.004 (0.040)	
		20%	0.005 (0.141)	0.001 (0.106)	0.004 (0.074)	0.000 (0.054)	0.002 (0.040)	
		40%	0.002 (0.144)	0.000 (0.104)	0.004 (0.075)	0.002 (0.055)	0.003 (0.041)	

Note: N = Sample Size; T = measurement occasions; ES = Effect Size, PMD = Planned-Missing Data Rate. See Figure 4.3.3 for the parameters of interest. The values without the parenthesis represent the mean of the five intercepts averaged across successful replications and the values within the parenthesis represent the standard deviation of the intercepts parameter across successful replications.

D.3.2 2-1-1 Mediation Model

Table D.3: 2-1-1 Mediation Model Level-2 Disturbance Correlation $\sigma = 0$

T	ES	PMD	N				
			25	50	100	200	350
			σ_{MY}				
30	0.3	0%	0.001 (0.049)	0.002 (0.034)	0.001 (0.023)	0.000 (0.017)	0.001 (0.013)
		20%	0.001 (0.052)	0.000 (0.035)	0.001 (0.024)	0.001 (0.018)	0.001 (0.013)
		40%	0.002 (0.055)	0.002 (0.038)	0.001 (0.026)	0.000 (0.018)	0.001 (0.015)
	0.6	0%	0.003 (0.049)	0.004 (0.035)	0.002 (0.026)	0.001 (0.018)	0.000 (0.013)
		20%	-0.002 (0.052)	0.001 (0.038)	0.003 (0.027)	0.002 (0.019)	0.001 (0.014)
		40%	0.002 (0.058)	0.005 (0.043)	0.003 (0.030)	0.002 (0.021)	0.000 (0.015)
60	0.3	0%	0.000 (0.034)	-0.001 (0.024)	0.000 (0.015)	0.001 (0.011)	0.001 (0.009)
		20%	-0.001 (0.034)	0.002 (0.025)	-0.001 (0.016)	0.000 (0.012)	0.001 (0.009)
		40%	-0.001 (0.037)	0.002 (0.028)	-0.001 (0.018)	0.001 (0.013)	0.000 (0.010)
	0.6	0%	0.000 (0.035)	-0.002 (0.024)	0.000 (0.018)	0.000 (0.012)	0.001 (0.009)
		20%	0.000 (0.037)	0.000 (0.027)	0.001 (0.019)	-0.001 (0.013)	0.000 (0.009)
		40%	0.000 (0.043)	-0.002 (0.029)	0.000 (0.021)	0.000 (0.014)	0.000 (0.010)

Note: N = Sample Size; T = measurement occasions; ES = Effect Size, PMD = Planned-Missing Data Rate. See Figure 4.3.4 for the parameters of interest σ_{MY} . The values without the parenthesis represent the mean of the parameter averaged across successful replications and the values within the parenthesis represent the standard deviation of the parameter across successful replications.

Table D.4: 2-1-1 Mediation Model Level-2 Indicator Intercepts $\mu = 0$

T	ES	PMD	N					
			25	50	100	200	350	
μ_M								
30	0.3	0%	0.045 (0.151)	0.010 (0.122)	-0.005 (0.088)	0.005 (0.060)	0.000 (0.044)	
		20%	0.047 (0.149)	0.025 (0.121)	-0.001 (0.088)	-0.001 (0.060)	0.001 (0.044)	
		40%	0.046 (0.152)	0.017 (0.124)	0.000 (0.089)	0.005 (0.061)	0.003 (0.045)	
	0.6	0%	0.084 (0.148)	0.042 (0.115)	0.006 (0.079)	0.007 (0.057)	-0.001 (0.043)	
		20%	0.087 (0.147)	0.052 (0.114)	0.010 (0.079)	0.001 (0.057)	0.001 (0.043)	
		40%	0.082 (0.149)	0.057 (0.115)	0.011 (0.082)	0.008 (0.058)	0.002 (0.044)	
	60	0.3	0%	0.036 (0.151)	0.018 (0.110)	0.005 (0.082)	-0.002 (0.060)	0.002 (0.045)
			20%	0.038 (0.151)	0.011 (0.111)	-0.009 (0.083)	0.000 (0.061)	-0.002 (0.045)
			40%	0.045 (0.149)	0.011 (0.109)	0.005 (0.083)	0.005 (0.061)	0.003 (0.045)
0.6		0%	0.076 (0.150)	0.045 (0.118)	0.009 (0.076)	0.003 (0.057)	0.004 (0.040)	
		20%	0.089 (0.140)	0.044 (0.120)	-0.002 (0.075)	0.006 (0.057)	0.001 (0.040)	
		40%	0.090 (0.144)	0.048 (0.120)	0.009 (0.076)	0.008 (0.057)	0.005 (0.041)	
μ_Y								
30	0.3	0%	0.009 (0.161)	0.007 (0.120)	0.001 (0.086)	-0.004 (0.060)	-0.002 (0.046)	
		20%	0.010 (0.166)	0.025 (0.124)	0.004 (0.086)	-0.007 (0.061)	0.000 (0.046)	
		40%	0.018 (0.166)	0.008 (0.122)	-0.001 (0.088)	0.000 (0.062)	-0.004 (0.047)	
	0.6	0%	0.064 (0.166)	0.027 (0.113)	0.009 (0.078)	0.006 (0.057)	0.001 (0.043)	
		20%	0.063 (0.171)	0.032 (0.113)	0.016 (0.080)	0.002 (0.058)	0.003 (0.043)	
		40%	0.059 (0.172)	0.030 (0.116)	0.012 (0.081)	0.009 (0.059)	0.001 (0.044)	
	60	0.3	0%	0.028 (0.160)	0.004 (0.119)	0.003 (0.080)	0.004 (0.061)	0.006 (0.043)
			20%	0.022 (0.162)	-0.004 (0.120)	0.001 (0.081)	0.002 (0.061)	0.004 (0.043)
			40%	0.011 (0.164)	-0.006 (0.118)	0.005 (0.081)	0.001 (0.062)	0.007 (0.044)
0.6		0%	0.056 (0.157)	0.029 (0.108)	0.005 (0.079)	0.006 (0.057)	0.003 (0.042)	
		20%	0.048 (0.155)	0.023 (0.112)	0.002 (0.079)	0.006 (0.057)	0.001 (0.042)	
		40%	0.046 (0.156)	0.023 (0.110)	0.009 (0.080)	0.007 (0.058)	0.004 (0.043)	

Note: N = Sample Size; T = measurement occasions; ES = Effect Size, PMD = Planned-Missing Data Rate. See Figure 4.3.4 for the parameters of interest. The values without the parenthesis represent the mean of the five intercepts averaged across successful replications and the values within the parenthesis represent the standard deviation of the intercepts parameter across successful replications.

Appendix E

Study 3 Materials

E.1 Data Generating Scripts

E.1.1 Step 1

```
library(foreach)
library(dplyr)

ScriptDir <- "H:/Scripts"
datadir <- "H:/DataAndOutput"

# read in Jmplus Template Input File
template <- readLines("TVEM_template.inp")
```

```

# custom function to edit data-generating template input file
prep <- function(){
  folder <- paste0("N", sample,
                  "T", timepoint,
                  "F", fixed*10,
                  "R", random*100)

  dir.create(folder)

  stringr::str_replace_all(template,
                           c("sample" = as.character(sample),
                             "timepoint" = as.character(timepoint),
                             "total_obs" = as.character(sample*timepoint),
                             "fixed" = as.character(fixed),
                             "random" = as.character(random),
                             "seednum" = as.character(round(runif(1, min = 1000, max = 9999)))))) %>%
    write.table(., file = file.path(getwd(), folder, "Data_Generating_Model.inp"),
               row.names = FALSE, col.names = FALSE, quote = FALSE)
}

# edit template
setwd(datadir)

set.seed(1234) # set seed for the generating seed number in the template

foreach(sample = c(50, 100, 200, 350)) %:%
  foreach(timepoint = c(15, 30, 60, 120)) %:%
    foreach(fixed = c(0.3, 0.6)) %:%
      foreach(random = c(0.16, 0.64)) %do% prep()

setwd(ScriptDir)

```

Mplus Template Input File

```

TITLE:
  TVEM (cross-classified model);

MONTECARLO:

```

```
NAMES ARE x1 m1 y1;
LAGGED ARE x1(1) m1(1) y1(1);
NCSIZES = 1[1];
CSIZES = sample[timepoint(1)];
NOBS = total_obs;
SEED = seednum;
NREP = 500;
REPSAVE = ALL;
SAVE = data_raw*.csv;
```

ANALYSIS:

```
TYPE IS CROSSCLASSIFIED RANDOM;
ESTIMATOR IS BAYES;
FBITER IS 100;
PROCESS IS 2;
```

MODEL POPULATION:

```
%WITHIN%
```

```
x1 ON x1&1*0.2;
m1 ON m1&1*0.2;
y1 ON y1&1*0.2;
```

```
x1@1; m1@1; y1@1;
x1 WITH m1*0; x1 WITH y1*0; m1 WITH y1*0;
```

```
S1 | m1 ON x1&1;
S2 | y1 ON x1&1;
S3 | y1 ON m1&1;
```

```
%BETWEEN level2a%
```

```
[S1-S3*fixed];
S1-S3*random;
S1 WITH S2*0; S2 WITH S3*0; S1 WITH S3*0;
```

```
x1-y1*0;
```

```
%BETWEEN level2b%
```

```
[S1-S3*0]; S1-S3*0;
```

```

[x1-y1*0]; x1-y1*0.5;
MODEL:
%WITHIN%
x1 ON x1&1*0.2;
m1 ON m1&1*0.2;
y1 ON y1&1*0.2;

x1*1; m1*1; y1*1;

S1 | m1 ON x1&1;
S2 | y1 ON x1&1;
S3 | y1 ON m1&1;

%BETWEEN level2a%
[S1-S3*fixed];
S1-S3*random;
x1-y1*0;

%BETWEEN level2b%
[S1-S3@0]; S1-S3*0;
[x1-y1*0]; x1-y1*0.5;

OUTPUT:
TECH8 TECH9;

```

E.1.2 Step 2

```

#### 03 Convert Raw to Indicators #####

ScriptDir <- "H:/Scripts"
DataDir <- "H:/DataAndOutput"
setwd(ScriptDir)
source("design.R") # function to create design matrix for missing data
source("convert_raw.R") # function to convert mplus raw data

```

```

# get data folder names
setwd(DataDir)
folders <- list.dirs(getwd(), full.names = FALSE, recursive = FALSE)

for (folder in folders){

  # set working dir to folder
  setwd(file.path(DataDir, folder))

  # check if there are already subfolders for reliability and % missing
  subfolders <- list.dirs(getwd(), full.names = FALSE, recursive = FALSE)

  if (length(subfolders) == 0){

    # read data_raw* and convert them based on omega and missingness and put them in the new folder
    datafiles <- list.files(getwd(), pattern = ".csv")[-501]

    if (length(datafiles) == 500){

      # grab simulation information
      sim_info <- as.numeric(unlist(regmatches(folder, gregexpr("[:digit:]]+", folder))))

      # reliabilty (0.6 vs. 0.78), and missing (0%, 20%, 40%)
      for (omega in c(0.6, 0.8)){
        for (missing in c(0, 20, 40)){

          # create design matrix for missing data
          if (missing == 0){
            dm <- 1
          } else {dm <- design(n = sim_info[1], t = sim_info[2], missing = missing)}

          # create new folder
          newfolder <- paste0("R", omega*10, "M", missing)
          dir.create(newfolder)

          for (dat in datafiles){
            data_converted <- convert(omega = omega, data = dat, N = sim_info[1], TP = sim_info[2], dm =
              dm)
          }
        }
      }
    }
  }
}

```

```

        write.table(data_converted, file = file.path(DataDir, folder, newfolder, paste0("data", readr
          ::parse_number(dat), ".csv")),
          sep = ",", row.names = FALSE, col.names = FALSE)
      }
    } # end of missing
  } # end of omega
} else{cat("There is not enough data in", folder, "yet \n")}
} else{cat("All subfolders and indicators in", folder, "have been created \n")}
} # end of folders

```

Custom R Function: *design()*

```

design <- function(n, t, missing){

  # set up "forms": x1-x5 m1-m5 y1-y5
  # setA = XAB or XA
  # SetB = XAC or XB
  # SetC = XBC OR XC
  if (missing == 20){
    setA <- c(1, 1, 1, 1, 0, 1, 1, 1, 1, 0, 1, 1, 1, 1, 0)
    setB <- c(1, 1, 1, 0, 1, 1, 1, 1, 0, 1, 1, 1, 1, 0, 1)
    setC <- c(1, 1, 0, 1, 1, 1, 1, 0, 1, 1, 1, 1, 0, 1, 1)
  } else if (missing == 40){
    setA <- c(1, 1, 1, 0, 0, 1, 1, 1, 0, 0, 1, 1, 1, 0, 0)
    setB <- c(1, 1, 0, 1, 0, 1, 1, 0, 1, 0, 1, 1, 0, 1, 0)
    setC <- c(1, 1, 0, 0, 1, 1, 1, 0, 0, 1, 1, 1, 0, 0, 1)
  }

  # set up distribution patterns given measurement occasion
  # pattern 1 = setA--> setB --> setC
  # pattern 2 = setB--> setC --> setA
  # pattern 3 = setC--> setA --> setB

  pattern_1 <- NULL
  times <- 1
  while (times <= t/3){
    pattern_1 <- rbind(pattern_1, setA)
  }
}

```

```
pattern_1 <- rbind(pattern_1, setB)
pattern_1 <- rbind(pattern_1, setC)

times <- times + 1
}

pattern_2 <- NULL
times <- 1
while (times <= t/3){
  pattern_2 <- rbind(pattern_2, setB)
  pattern_2 <- rbind(pattern_2, setC)
  pattern_2 <- rbind(pattern_2, setA)

  times <- times + 1
}

pattern_3 <- NULL
times <- 1
while (times <= t/3){
  pattern_3 <- rbind(pattern_3, setC)
  pattern_3 <- rbind(pattern_3, setA)
  pattern_3 <- rbind(pattern_3, setB)

  times <- times + 1
}

# set up design matrix depending on sample size
# pattern_1 --> pattern_2 --> pattern_3 --> pattern_1 --> loop
design_matrix <- NULL
sample <- 1
while (sample <= ceiling(n/3)){
  design_matrix <- rbind(design_matrix, pattern_1)
  design_matrix <- rbind(design_matrix, pattern_2)
  design_matrix <- rbind(design_matrix, pattern_3)

  sample <- sample + 1
}
design_matrix <- design_matrix[1:(n*t), ]
```

```

design_matrix <- cbind(design_matrix, 1, 1)
return(design_matrix)
}

```

Custom R Function: *convert()*

```

convert <- function(omega, data, N, TP, dm){
  library(dplyr)

  # read data
  dat <- read.csv(data, header = FALSE, sep = "")
  names(dat) <- c("X", "M", "Y", "Time", "Individual", "X_lag1", "M_lag1", "Y_ag1")

  # obtain observed variance of X, M, and Y at each time point
  var_at_time <- dat %>%
    group_by(Time) %>%
    summarise(var_x = var(X),
              var_m = var(M),
              var_y = var(Y))

  loadings <- 1

  errvars <- ((1 - omega)*(loadings*5)^2*var_at_time[, c("var_x", "var_m", "var_y")])/(5*omega)
  errvar_vector <- as.vector(t(as.matrix(errvars)))
  errvar_vector_expand <- rep(errvar_vector, each = 5)

  sigma <- diag(3*5*TP)
  diag(sigma) <- errvar_vector_expand
  errs <- data.frame(MASS::mvrnorm(n = N, mu = rep(0, 3*5*TP), Sigma = sigma, empirical = FALSE))
  errs$Individual <- 1:nrow(errs)

  # split dat by individual, generate observed score
  dat_indi_split <- split(dat, f = as.factor(dat$Individual))
  errs_indi_split <- split(errs, f = as.factor(errs$Individual))

  out <- NULL

```

```

for (ii in 1:length(dat_indi_split)){
  indi_tmpt <- dat_indi_split[[ii]][1:3] * loadings
  indi_tmpt_expand <- with(indi_tmpt, data.frame(x1 = X, x2 = X, x3 = X, x4 = X, x5 = X,
                                                m1 = M, m2 = M, m3 = M, m4 = M, m5 = M,
                                                y1 = Y, y2 = Y, y3 = Y, y4 = Y, y5 = Y))

  error_tmpt <- as.matrix(errs_indi_split[[ii]][1, 1:3*5*TP])
  error_tmpt <- matrix(error_tmpt, nrow = TP, ncol = 15, byrow = TRUE)

  out[[ii]] <- indi_tmpt_expand + error_tmpt
  out[[ii]][ "Time" ] <- 1:TP
  out[[ii]][ "Individual" ] <- ii
}

final_data <- do.call(rbind, out)

# Create data with missing data (if any)
final_data_missing <- final_data * dm
final_data_missing[which(final_data_missing == 0, arr.ind = TRUE)] <- NA

final_data_missing <- final_data_missing %>%
  mutate(x = rowMeans(select(., starts_with("x")), na.rm = TRUE),
         m = rowMeans(select(., starts_with("m")), na.rm = TRUE),
         y = rowMeans(select(., starts_with("y")), na.rm = TRUE)) %>%
  select(x, m, y, Time, Individual)

return(final_data_missing)
}

```

E.2 Mplus Input File For Model Fitting

```

TITLE:
  TVEM (cross-classified model);

DATA:
  FILE IS data.csv;

```

```

VARIABLE:
  NAMES ARE x1 m1 y1 time id;
  LAGGED ARE x1(1) m1(1) y1(1);
  USEVAR ARE x1 m1 y1;
  CLUSTER IS id time; ! level2b = id, level2a = time (time within id)

ANALYSIS:
  TYPE IS CROSSCLASSIFIED RANDOM;
  ESTIMATOR IS BAYES;
  BITER IS 4000 (2500);
  PROCESS IS 2;

MODEL:
  %WITHIN%
  x1 ON x1&1;
  m1 ON m1&1;
  y1 ON y1&1;

  x1; m1; y1;

  S1 | m1 ON x1&1;
  S2 | y1 ON x1&1;
  S3 | y1 ON m1&1;

  %BETWEEN time%
  [S1-S3];      ! mean slope
  S1-S3;        ! variance slope
  [x1-y1@0];    ! mean intercept
  x1-y1;        ! variance intercept

  %BETWEEN id%
  [S1-S3@0];    ! mean slope
  S1-S3;        ! variance slope
  [x1-y1];      ! mean intercept
  x1-y1;        ! variance intercept

OUTPUT:
  TECH8 CINT(HPD);

```

PLOT:
TYPE IS PLOT2;

E.3 Within-Level Over-specified Parameters

Table E.1: Descriptive Statistics for Within-Level Disturbance Covariance $\sigma_{XM} = 0$

FE	RE	T	PMD	$\omega = 0.60$			$\omega = 0.80$			
				50	N 100	200	50	N 100	200	
0.3	0.16	15	0%	0.002 (0.041)	0.002 (0.027)	0.000 (0.019)	σ_{XM}	0.003 (0.041)	0.003 (0.027)	0.001 (0.019)
			20%	-0.168 (0.075)	-0.165 (0.055)	-0.166 (0.041)	-0.058 (0.051)	-0.058 (0.036)	-0.060 (0.025)	
			40%	-0.132 (0.067)	-0.135 (0.051)	-0.136 (0.041)	-0.059 (0.049)	-0.060 (0.034)	-0.062 (0.027)	
			30	0%	0.001 (0.028)	0.000 (0.018)	0.001 (0.013)	0.001 (0.028)	0.000 (0.018)	0.001 (0.013)
				20%	-0.152 (0.060)	-0.154 (0.044)	-0.152 (0.036)	-0.054 (0.036)	-0.054 (0.026)	-0.053 (0.018)
				40%	-0.134 (0.052)	-0.139 (0.040)	-0.141 (0.033)	-0.063 (0.037)	-0.066 (0.026)	-0.066 (0.021)
		60	0%	0.002 (0.018)	0.000 (0.013)	0.001 (0.009)	0.002 (0.018)	0.000 (0.013)	0.001 (0.009)	
			20%	-0.146 (0.049)	-0.147 (0.040)	-0.145 (0.033)	-0.051 (0.025)	-0.051 (0.020)	-0.050 (0.014)	
			40%	-0.137 (0.038)	-0.136 (0.031)	-0.135 (0.024)	-0.064 (0.026)	-0.066 (0.020)	-0.065 (0.014)	
		120	0%	0.001 (0.013)	-0.001 (0.009)	0.000 (0.007)	0.001 (0.013)	0.000 (0.009)	0.000 (0.007)	
			20%	-0.149 (0.047)	-0.145 (0.037)	-0.146 (0.032)	-0.051 (0.021)	-0.051 (0.015)	-0.051 (0.014)	
			40%	-0.132 (0.031)	-0.132 (0.026)	-0.133 (0.023)	-0.066 (0.021)	-0.065 (0.016)	-0.065 (0.014)	
		0.64	15	0%	-0.002 (0.041)	0.002 (0.029)	0.000 (0.020)	-0.002 (0.041)	0.003 (0.029)	0.000 (0.020)
				20%	-0.333 (0.189)	-0.312 (0.154)	-0.323 (0.159)	-0.113 (0.079)	-0.105 (0.063)	-0.107 (0.058)
				40%	-0.178 (0.124)	-0.171 (0.092)	-0.176 (0.101)	-0.095 (0.073)	-0.092 (0.057)	-0.093 (0.053)
				30	0%	0.000 (0.028)	0.001 (0.021)	0.000 (0.013)	0.000 (0.028)	0.001 (0.021)
			20%		-0.300 (0.145)	-0.293 (0.157)	-0.299 (0.149)	-0.101 (0.060)	-0.098 (0.059)	-0.103 (0.053)
			40%		-0.175 (0.083)	-0.177 (0.084)	-0.179 (0.073)	-0.094 (0.053)	-0.096 (0.048)	-0.096 (0.040)
			60	0%	0.001 (0.019)	0.001 (0.013)	0.001 (0.009)	0.001 (0.019)	0.001 (0.013)	0.001 (0.009)
				20%	-0.290 (0.166)	-0.276 (0.121)	-0.289 (0.149)	-0.096 (0.059)	-0.094 (0.044)	-0.098 (0.055)
				40%	-0.169 (0.068)	-0.168 (0.055)	-0.176 (0.062)	-0.092 (0.040)	-0.091 (0.034)	-0.093 (0.032)
			120	0%	0.001 (0.014)	0.001 (0.009)	0.000 (0.006)	0.001 (0.014)	0.001 (0.009)	0.000 (0.006)
				20%	-0.276 (0.146)	-0.282 (0.135)	-0.278 (0.137)	-0.093 (0.052)	-0.095 (0.050)	-0.094 (0.048)
				40%	-0.165 (0.055)	-0.164 (0.046)	-0.163 (0.047)	-0.090 (0.033)	-0.090 (0.029)	-0.090 (0.028)
0.6	0.16	15	0%	-0.007 (0.038)	0.002 (0.027)	-0.001 (0.019)	-0.004 (0.040)	0.003 (0.026)	0.000 (0.018)	
		20%	-0.239 (0.104)	-0.221 (0.080)	-0.225 (0.078)	-0.075 (0.055)	-0.067 (0.041)	-0.067 (0.032)		
		40%	-0.071 (0.072)	-0.077 (0.058)	-0.074 (0.049)	-0.045 (0.050)	-0.036 (0.038)	-0.040 (0.027)		
		30	0%	0.002 (0.029)	0.000 (0.019)	0.001 (0.013)	0.002 (0.029)	0.001 (0.020)	0.001 (0.013)	
	20%		-0.200 (0.096)	-0.198 (0.076)	-0.210 (0.070)	-0.053 (0.039)	-0.060 (0.032)	-0.061 (0.027)		
	40%		-0.057 (0.048)	-0.072 (0.041)	-0.071 (0.038)	-0.033 (0.036)	-0.039 (0.028)	-0.039 (0.022)		
	60	0%	-0.001 (0.019)	0.000 (0.013)	0.000 (0.010)	0.000 (0.019)	0.000 (0.013)	0.000 (0.010)		
		20%	-0.192 (0.080)	-0.192 (0.064)	-0.193 (0.061)	-0.055 (0.031)	-0.058 (0.024)	-0.057 (0.022)		
		40%	-0.067 (0.037)	-0.070 (0.031)	-0.070 (0.026)	-0.040 (0.025)	-0.041 (0.020)	-0.039 (0.016)		
	120	0%	-0.003 (0.013)	0.001 (0.009)	0.000 (0.006)	-0.003 (0.013)	0.001 (0.009)	0.000 (0.006)		
		20%	-0.194 (0.076)	-0.183 (0.064)	-0.187 (0.064)	-0.059 (0.030)	-0.055 (0.023)	-0.055 (0.019)		
		40%	-0.050 (0.030)	-0.067 (0.022)	-0.066 (0.017)	-0.047 (0.012)	-0.038 (0.015)	-0.039 (0.011)		
0.64	15	0%	-0.003 (0.040)	0.003 (0.027)	0.000 (0.019)	-0.004 (0.040)	0.004 (0.027)	0.000 (0.019)		
		20%	-0.395 (0.258)	-0.414 (0.258)	-0.430 (0.313)	-0.122 (0.102)	-0.121 (0.094)	-0.126 (0.105)		
		40%	-0.065 (0.130)	-0.076 (0.110)	-0.058 (0.118)	-0.041 (0.080)	-0.045 (0.059)	-0.042 (0.056)		
		30	0%	0.001 (0.026)	0.001 (0.019)	0.001 (0.013)	0.001 (0.026)	0.001 (0.018)	0.001 (0.013)	
	20%		-0.377 (0.255)	-0.371 (0.222)	-0.389 (0.248)	-0.109 (0.088)	-0.107 (0.073)	-0.117 (0.091)		
	40%		-0.064 (0.087)	-0.067 (0.083)	-0.070 (0.079)	-0.044 (0.053)	-0.046 (0.042)	-0.048 (0.039)		
	60	0%	0.000 (0.020)	0.002 (0.013)	0.000 (0.010)	0.000 (0.020)	0.002 (0.013)	0.000 (0.010)		
		20%	-0.376 (0.290)	-0.356 (0.228)	-0.365 (0.232)	-0.109 (0.088)	-0.102 (0.071)	-0.111 (0.079)		
		40%	-0.069 (0.064)	-0.071 (0.058)	-0.070 (0.062)	-0.046 (0.039)	-0.047 (0.034)	-0.047 (0.028)		
	120	0%	0.000 (0.013)	0.001 (0.009)	0.000 (0.007)	0.000 (0.013)	0.001 (0.009)	0.000 (0.007)		
		20%	-0.356 (0.243)	-0.354 (0.228)	-0.375 (0.293)	-0.107 (0.081)	-0.103 (0.072)	-0.115 (0.107)		
		40%	-0.065 (0.041)	-0.061 (0.035)	-0.058 (0.039)	-0.046 (0.027)	-0.043 (0.022)	-0.042 (0.022)		

Note: FE = Fixed Effect; N = Sample Size; T = Measurement Occasions; PMD = Planned-Missing Data Percentage; ω = Reliability. The values outside the brackets represent the average point-estimate of the parameter across the successful replications. The values enclosed in the brackets represent the average standard deviation of the posterior distribution of the parameter across the successful replications.

Table E.2: Descriptive Statistics for Within-Level Disturbance Covariance $\sigma_{XY} = 0$

FE	RE	T	PMD	$\omega = 0.60$			$\omega = 0.80$		
				50	N 100	200	50	N 100	200
σ_{XY}									
0.3	0.16	15	0%	-0.002 (0.042)	-0.001 (0.029)	-0.001 (0.020)	0.000 (0.042)	0.000 (0.028)	0.001 (0.020)
			20%	-0.143 (0.069)	-0.141 (0.051)	-0.144 (0.045)	-0.065 (0.052)	-0.066 (0.036)	-0.066 (0.029)
			40%	-0.153 (0.070)	-0.155 (0.059)	-0.149 (0.047)	-0.066 (0.055)	-0.066 (0.038)	-0.065 (0.029)
		30	0%	-0.002 (0.027)	0.000 (0.020)	0.000 (0.013)	-0.001 (0.027)	0.000 (0.020)	0.000 (0.013)
			20%	-0.146 (0.046)	-0.145 (0.040)	-0.147 (0.034)	-0.072 (0.035)	-0.068 (0.027)	-0.069 (0.021)
			40%	-0.129 (0.050)	-0.130 (0.040)	-0.130 (0.033)	-0.059 (0.034)	-0.056 (0.028)	-0.057 (0.020)
		60	0%	-0.002 (0.020)	-0.001 (0.013)	-0.001 (0.010)	-0.002 (0.020)	-0.001 (0.013)	-0.001 (0.010)
			20%	-0.151 (0.042)	-0.147 (0.032)	-0.147 (0.027)	-0.072 (0.028)	-0.070 (0.021)	-0.069 (0.018)
			40%	-0.122 (0.040)	-0.120 (0.032)	-0.120 (0.026)	-0.055 (0.027)	-0.054 (0.020)	-0.055 (0.016)
		120	0%	0.001 (0.013)	0.000 (0.009)	-0.001 (0.006)	0.001 (0.013)	0.000 (0.009)	-0.001 (0.006)
			20%	-0.147 (0.035)	-0.146 (0.028)	-0.148 (0.024)	-0.069 (0.022)	-0.069 (0.017)	-0.071 (0.014)
			40%	-0.115 (0.032)	-0.116 (0.026)	-0.117 (0.022)	-0.051 (0.021)	-0.051 (0.015)	-0.052 (0.012)
0.64	0.64	15	0%	-0.002 (0.042)	0.000 (0.031)	-0.001 (0.021)	-0.001 (0.041)	0.001 (0.031)	0.000 (0.021)
			20%	-0.212 (0.143)	-0.205 (0.122)	-0.214 (0.125)	-0.107 (0.079)	-0.102 (0.064)	-0.105 (0.065)
			40%	-0.297 (0.175)	-0.285 (0.141)	-0.288 (0.140)	-0.122 (0.087)	-0.114 (0.072)	-0.115 (0.065)
		30	0%	0.001 (0.027)	0.000 (0.021)	-0.001 (0.013)	0.001 (0.027)	0.001 (0.021)	-0.001 (0.013)
			20%	-0.225 (0.105)	-0.210 (0.089)	-0.214 (0.103)	-0.111 (0.062)	-0.106 (0.052)	-0.109 (0.052)
			40%	-0.257 (0.129)	-0.250 (0.111)	-0.254 (0.117)	-0.107 (0.067)	-0.102 (0.053)	-0.104 (0.049)
		60	0%	0.000 (0.019)	0.000 (0.014)	-0.001 (0.010)	0.000 (0.019)	0.000 (0.014)	-0.001 (0.010)
			20%	-0.212 (0.081)	-0.214 (0.075)	-0.220 (0.081)	-0.107 (0.047)	-0.108 (0.041)	-0.111 (0.044)
			40%	-0.237 (0.113)	-0.226 (0.086)	-0.248 (0.121)	-0.098 (0.053)	-0.096 (0.043)	-0.100 (0.047)
		120	0%	0.001 (0.014)	0.000 (0.009)	-0.001 (0.007)	0.001 (0.014)	0.000 (0.009)	-0.001 (0.007)
			20%	-0.205 (0.069)	-0.211 (0.067)	-0.211 (0.063)	-0.103 (0.042)	-0.106 (0.038)	-0.107 (0.036)
			40%	-0.226 (0.106)	-0.227 (0.085)	-0.222 (0.088)	-0.094 (0.048)	-0.097 (0.041)	-0.096 (0.042)
0.6	0.16	15	0%	-0.005 (0.042)	-0.005 (0.028)	-0.003 (0.020)	-0.006 (0.044)	-0.004 (0.028)	-0.002 (0.020)
			20%	-0.230 (0.088)	-0.221 (0.075)	-0.222 (0.071)	-0.113 (0.061)	-0.109 (0.048)	-0.106 (0.040)
			40%	-0.073 (0.088)	-0.061 (0.065)	-0.052 (0.050)	-0.030 (0.058)	-0.024 (0.040)	-0.021 (0.031)
		30	0%	-0.004 (0.026)	0.001 (0.020)	-0.001 (0.013)	-0.004 (0.027)	0.002 (0.020)	-0.001 (0.013)
			20%	-0.232 (0.075)	-0.226 (0.059)	-0.234 (0.057)	-0.110 (0.042)	-0.108 (0.036)	-0.113 (0.031)
			40%	-0.012 (0.056)	-0.012 (0.046)	-0.013 (0.037)	-0.007 (0.041)	-0.001 (0.030)	-0.003 (0.024)
		60	0%	-0.001 (0.021)	0.000 (0.013)	0.001 (0.009)	-0.001 (0.022)	0.000 (0.013)	0.001 (0.009)
			20%	-0.234 (0.060)	-0.233 (0.052)	-0.233 (0.049)	-0.113 (0.037)	-0.113 (0.030)	-0.112 (0.029)
			40%	-0.003 (0.047)	-0.001 (0.031)	-0.001 (0.026)	-0.005 (0.030)	0.003 (0.021)	0.003 (0.016)
		120	0%	0.000 (0.013)	-0.001 (0.009)	-0.001 (0.006)	-0.001 (0.013)	0.000 (0.009)	-0.001 (0.006)
			20%	-0.235 (0.056)	-0.229 (0.047)	-0.231 (0.046)	-0.117 (0.035)	-0.114 (0.028)	-0.112 (0.024)
			40%	0.030 (0.029)	0.001 (0.023)	-0.001 (0.019)	0.004 (0.020)	0.004 (0.016)	0.003 (0.012)
0.64	0.64	15	0%	-0.004 (0.042)	-0.001 (0.029)	-0.003 (0.021)	-0.003 (0.042)	0.000 (0.029)	-0.003 (0.021)
			20%	-0.319 (0.191)	-0.312 (0.173)	-0.338 (0.174)	-0.158 (0.103)	-0.156 (0.090)	-0.169 (0.092)
			40%	-0.149 (0.166)	-0.130 (0.144)	-0.126 (0.142)	-0.047 (0.092)	-0.035 (0.072)	-0.038 (0.083)
		30	0%	-0.006 (0.026)	0.000 (0.018)	-0.002 (0.013)	-0.006 (0.027)	0.000 (0.018)	-0.002 (0.013)
			20%	-0.344 (0.158)	-0.330 (0.141)	-0.343 (0.150)	-0.172 (0.090)	-0.163 (0.076)	-0.172 (0.081)
			40%	-0.100 (0.115)	-0.094 (0.125)	-0.088 (0.128)	-0.035 (0.057)	-0.025 (0.058)	-0.027 (0.056)
		60	0%	-0.002 (0.020)	-0.001 (0.014)	0.000 (0.009)	-0.002 (0.020)	-0.001 (0.014)	0.000 (0.009)
			20%	-0.341 (0.149)	-0.338 (0.135)	-0.337 (0.128)	-0.169 (0.080)	-0.166 (0.069)	-0.166 (0.068)
			40%	-0.067 (0.089)	-0.063 (0.081)	-0.073 (0.103)	-0.020 (0.055)	-0.018 (0.037)	-0.017 (0.038)
		120	0%	0.000 (0.013)	0.000 (0.009)	-0.001 (0.006)	0.000 (0.013)	0.000 (0.009)	-0.001 (0.006)
			20%	-0.328 (0.122)	-0.332 (0.129)	-0.342 (0.140)	-0.161 (0.067)	-0.162 (0.063)	-0.169 (0.074)
			40%	-0.069 (0.063)	-0.057 (0.057)	-0.066 (0.065)	-0.018 (0.035)	-0.015 (0.029)	-0.017 (0.025)

Note: FE = Fixed Effect; N = Sample Size; T = Measurement Occasions; PMD = Planned-Missing Data Percentage; ω = Reliability. The values outside the brackets represent the average point-estimate of the parameter across the successful replications. The values enclosed in the brackets represent the average standard deviation of the posterior distribution of the parameter across the successful replications.

Table E.3: Descriptive Statistics for Within-Level Disturbance Covariance $\sigma_{MY} = 0$

FE	RE	T	PMD	$\omega = 0.60$			$\omega = 0.80$		
				50	N 100	200	50	N 100	200
σ_{MY}									
0.3	0.16	15	0%	0.004 (0.041)	0.003 (0.027)	0.003 (0.019)	0.004 (0.041)	0.004 (0.028)	0.004 (0.019)
			20%	-0.134 (0.069)	-0.133 (0.052)	-0.138 (0.046)	-0.060 (0.050)	-0.062 (0.038)	-0.062 (0.028)
			40%	-0.144 (0.070)	-0.144 (0.050)	-0.146 (0.042)	-0.077 (0.057)	-0.077 (0.039)	-0.078 (0.028)
		30	0%	0.002 (0.029)	0.001 (0.020)	0.001 (0.014)	0.002 (0.029)	0.001 (0.020)	0.001 (0.014)
			20%	-0.125 (0.049)	-0.125 (0.039)	-0.126 (0.031)	-0.056 (0.036)	-0.059 (0.027)	-0.059 (0.020)
			40%	-0.146 (0.048)	-0.150 (0.042)	-0.150 (0.034)	-0.079 (0.038)	-0.083 (0.030)	-0.082 (0.023)
		60	0%	0.000 (0.019)	0.001 (0.013)	0.000 (0.010)	0.000 (0.019)	0.001 (0.013)	0.000 (0.010)
			20%	-0.121 (0.036)	-0.119 (0.028)	-0.120 (0.023)	-0.058 (0.027)	-0.057 (0.019)	-0.058 (0.016)
			40%	-0.147 (0.036)	-0.147 (0.028)	-0.147 (0.025)	-0.082 (0.027)	-0.081 (0.021)	-0.081 (0.018)
		120	0%	0.000 (0.013)	0.000 (0.009)	0.000 (0.007)	0.000 (0.013)	0.000 (0.009)	0.000 (0.007)
			20%	-0.118 (0.029)	-0.115 (0.023)	-0.116 (0.020)	-0.057 (0.020)	-0.054 (0.014)	-0.056 (0.012)
			40%	-0.146 (0.029)	-0.143 (0.023)	-0.145 (0.021)	-0.082 (0.024)	-0.080 (0.017)	-0.081 (0.014)
0.64	0.16	15	0%	0.004 (0.042)	-0.002 (0.031)	0.000 (0.022)	0.005 (0.042)	-0.001 (0.031)	0.000 (0.021)
			20%	-0.178 (0.158)	-0.175 (0.133)	-0.186 (0.129)	-0.091 (0.090)	-0.092 (0.072)	-0.096 (0.065)
			40%	-0.205 (0.153)	-0.201 (0.131)	-0.200 (0.134)	-0.115 (0.099)	-0.118 (0.088)	-0.122 (0.081)
		30	0%	0.002 (0.028)	-0.001 (0.019)	0.000 (0.014)	0.002 (0.028)	0.000 (0.019)	0.001 (0.014)
			20%	-0.171 (0.109)	-0.171 (0.095)	-0.176 (0.092)	-0.088 (0.067)	-0.090 (0.053)	-0.092 (0.051)
			40%	-0.193 (0.109)	-0.199 (0.095)	-0.201 (0.093)	-0.116 (0.076)	-0.120 (0.063)	-0.121 (0.060)
		60	0%	-0.002 (0.020)	0.001 (0.013)	0.000 (0.009)	-0.002 (0.020)	0.001 (0.013)	0.000 (0.009)
			20%	-0.168 (0.073)	-0.161 (0.064)	-0.168 (0.066)	-0.091 (0.046)	-0.086 (0.037)	-0.091 (0.039)
			40%	-0.203 (0.076)	-0.193 (0.063)	-0.205 (0.066)	-0.121 (0.050)	-0.116 (0.046)	-0.119 (0.043)
		120	0%	0.000 (0.013)	0.000 (0.009)	0.000 (0.007)	0.000 (0.013)	0.000 (0.009)	0.000 (0.007)
			20%	-0.158 (0.060)	-0.159 (0.053)	-0.158 (0.050)	-0.084 (0.038)	-0.084 (0.032)	-0.083 (0.031)
			40%	-0.196 (0.059)	-0.189 (0.050)	-0.187 (0.048)	-0.117 (0.040)	-0.115 (0.036)	-0.114 (0.035)
0.6	0.16	15	0%	0.002 (0.040)	0.007 (0.030)	0.006 (0.021)	0.004 (0.041)	0.006 (0.030)	0.005 (0.021)
			20%	-0.130 (0.085)	-0.117 (0.068)	-0.121 (0.059)	-0.071 (0.060)	-0.063 (0.044)	-0.066 (0.037)
			40%	-0.127 (0.066)	-0.136 (0.059)	-0.138 (0.047)	-0.080 (0.054)	-0.079 (0.045)	-0.080 (0.036)
		30	0%	0.005 (0.027)	0.001 (0.019)	0.002 (0.015)	0.004 (0.027)	0.001 (0.019)	0.002 (0.015)
			20%	-0.110 (0.057)	-0.110 (0.045)	-0.106 (0.039)	-0.060 (0.038)	-0.063 (0.031)	-0.062 (0.026)
			40%	-0.134 (0.048)	-0.140 (0.039)	-0.140 (0.037)	-0.077 (0.038)	-0.082 (0.031)	-0.081 (0.027)
		60	0%	-0.001 (0.019)	-0.001 (0.014)	0.000 (0.009)	-0.001 (0.019)	0.000 (0.014)	0.000 (0.009)
			20%	-0.103 (0.041)	-0.099 (0.031)	-0.100 (0.025)	-0.059 (0.029)	-0.059 (0.023)	-0.057 (0.017)
			40%	-0.140 (0.038)	-0.140 (0.031)	-0.141 (0.025)	-0.083 (0.029)	-0.083 (0.024)	-0.081 (0.018)
		120	0%	0.000 (0.015)	0.001 (0.009)	0.001 (0.007)	0.000 (0.013)	0.001 (0.010)	0.001 (0.007)
			20%	-0.097 (0.030)	-0.092 (0.023)	-0.096 (0.020)	-0.056 (0.021)	-0.054 (0.017)	-0.054 (0.014)
			40%	-0.141 (0.039)	-0.138 (0.023)	-0.135 (0.021)	-0.073 (0.027)	-0.081 (0.019)	-0.081 (0.016)
0.64	0.16	15	0%	0.001 (0.041)	-0.002 (0.030)	-0.002 (0.022)	0.000 (0.042)	-0.001 (0.031)	-0.002 (0.022)
			20%	-0.103 (0.177)	-0.107 (0.158)	-0.111 (0.148)	-0.078 (0.102)	-0.078 (0.084)	-0.083 (0.077)
			40%	-0.161 (0.156)	-0.177 (0.134)	-0.174 (0.139)	-0.099 (0.102)	-0.110 (0.092)	-0.114 (0.088)
		30	0%	0.001 (0.028)	0.000 (0.019)	0.001 (0.013)	0.001 (0.028)	-0.001 (0.019)	0.001 (0.013)
			20%	-0.098 (0.131)	-0.104 (0.115)	-0.096 (0.114)	-0.070 (0.069)	-0.077 (0.063)	-0.074 (0.059)
			40%	-0.174 (0.093)	-0.177 (0.091)	-0.186 (0.089)	-0.109 (0.068)	-0.109 (0.064)	-0.112 (0.061)
		60	0%	0.000 (0.019)	0.001 (0.013)	0.000 (0.010)	0.000 (0.019)	0.001 (0.013)	0.000 (0.010)
			20%	-0.080 (0.097)	-0.083 (0.079)	-0.079 (0.079)	-0.066 (0.047)	-0.068 (0.041)	-0.064 (0.043)
			40%	-0.174 (0.073)	-0.179 (0.076)	-0.180 (0.069)	-0.108 (0.054)	-0.109 (0.052)	-0.106 (0.045)
		120	0%	0.001 (0.013)	0.001 (0.009)	0.000 (0.007)	0.001 (0.013)	0.001 (0.009)	0.000 (0.007)
			20%	-0.079 (0.061)	-0.082 (0.065)	-0.082 (0.068)	-0.062 (0.035)	-0.064 (0.032)	-0.065 (0.029)
			40%	-0.169 (0.054)	-0.171 (0.051)	-0.174 (0.052)	-0.108 (0.043)	-0.109 (0.039)	-0.108 (0.036)

Note: FE = Fixed Effect; N = Sample Size; T = Measurement Occasions; PMD = Planned-Missing Data Percentage; ω = Reliability. The values outside the brackets represent the average point-estimate of the parameter across the successful replications. The values enclosed in the brackets represent the average standard deviation of the posterior distribution of the parameter across the successful replications.