

Estimating Interaction Effects With Incomplete Predictor Variables

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The existing missing data literature does not provide a clear prescription for estimating interaction effects with missing data, particularly when the interaction involves a pair of continuous variables. In this article, we describe maximum likelihood and multiple imputation procedures for this common analysis problem. We outline 3 latent variable model specifications for interaction analyses with missing data. These models apply procedures from the latent variable interaction literature to analyses with a single indicator per construct (e.g., a regression analysis with scale scores). We also discuss multiple imputation for interaction effects, emphasizing an approach that applies standard imputation procedures to the product of 2 raw score predictors. We thoroughly describe the process of probing interaction effects with maximum likelihood and multiple imputation. For both missing data handling techniques, we outline centering and transformation strategies that researchers can implement in popular software packages, and we use a series of real data analyses to illustrate these methods. Finally, we use computer simulations to evaluate the performance of the proposed techniques.

Keywords: missing data, maximum likelihood estimation, multiple imputation, centering, interaction effects

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The last decade has seen increasing interest in “modern” missing data handling approaches that assume a missing at random (MAR) mechanism, whereby the probability of missing data on a variable y is related to other variables in the analysis model but not to the would-be values of y itself. Maximum likelihood estimation and multiple imputation are the principle MAR-based procedures in behavioral science applications, and both procedures are widely available in software packages. Although the missing data literature has grown rapidly in recent years, many practical issues remain unresolved. For example, the literature does not provide a clear prescription for estimating interaction effects with missing data. Methodologists have outlined multiple group procedures for situations where one of the interacting variables is categorical and complete (Enders, 2010; Enders & Gottschall, 2011; Graham, 2009), but missing data handling becomes more complicated when the interaction involves a pair of continuous variables. The purpose of this article is to describe maximum likelihood and multiple imputation procedures for this common analysis problem.

The structural equation model (SEM) framework is ideally suited for maximum likelihood estimation because it can accommodate incomplete predictors and outcomes. To take advantage of

this flexibility, we describe three latent variable model specifications for interaction analyses with missing data. These models apply procedures from the latent variable interaction literature (e.g., Jöreskog & Yang, 1996; Kenny & Judd, 1984; Marsh, Wen, & Hau, 2004, 2006) to regression models with measured variables. We also discuss multiple imputation for interaction effects, focusing on an approach that applies standard imputation procedures (e.g., data augmentation; Schafer, 1997) to the product of two raw score predictors.

To probe interaction effects, researchers can center predictor variables prior to analysis (Aiken & West, 1991) or transform estimates to the desired simple slopes (Bauer & Curran, 2005; Hayes & Matthes, 2009; Preacher, Curran, & Bauer, 2006). Missing data can complicate the application of these familiar techniques, and popular software programs may accommodate one approach but not the other. For both missing data handling techniques, we describe the process of probing interaction effects, and we outline centering and transformation strategies that researchers can implement in popular software packages. We use a series of real data analyses to illustrate these methods.

Finally, we use computer simulations to study the performance of the missing data handling methods for interaction effects. Maximum likelihood estimation and multiple imputation invoke assumptions that are necessarily violated when the analysis model includes a product variable (e.g., multivariate normality). Previous research suggests that MAR-based methods can yield consistent estimates when normality is violated (e.g., Demirtas, Freels, & Yucel, 2008; Enders, 2001; Savalei & Bentler, 2005; Yuan, 2009; Yuan & Bentler, 2010; Yuan & Zhang, 2012), but it is unclear whether this finding extends to interaction effects.

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Motivating Example

Throughout the article, we use data from [Montague, Enders, and Castro's \(2005\)](#) study that examined whether primary school academic achievement and teacher ratings of academic competence are predictive of middle school reading achievement. Our analyses are based on a sample of $N = 74$ adolescents who were identified as being at risk for developing emotional and behavioral disorders when they were in kindergarten and first grade. [Table 1](#) gives maximum likelihood estimates of the descriptive statistics and correlations. Notice that all variables are incomplete, and the primary school reading assessment has substantial missingness.

To illustrate interaction analyses with missing data, we consider a regression model where middle school reading achievement is predicted by teacher ratings of learning problems in primary school, primary school reading achievement, and their interaction, as follows:

$$\begin{aligned} \text{midread} = \alpha + \gamma_1(\text{primread}) + \gamma_2(\text{lnnprob}) \\ + \gamma_3(\text{primread})(\text{lnnprob}) + \zeta. \end{aligned}$$

To make the ensuing discussion as general as possible, we henceforth define primary school reading achievement (the focal predictor) as x and primary school learning problems (the moderator) as z . Using this generic notation, the regression model is

$$y = \alpha + \gamma_1(x) + \gamma_2(z) + \gamma_3(x)(z) + \zeta, \quad (1)$$

where α is the intercept, γ_1 and γ_2 are lower order (i.e., conditional) effects, γ_3 is the interaction effect, and ζ is the usual regression residual.

More than a decade ago, the American Psychological Association's Task Force on Statistical Inference warned that complete-case analyses are "among the worst methods available for practical applications" ([Wilkinson and the Task Force on Statistical Inference, American Psychological Association, Science Directorate, 1999](#), p. 598). Because this approach is still very common in published research articles, we began by analyzing the subsample of $n = 20$ complete cases. The estimates were as follows: $\hat{\alpha}_0 = 15.229$ ($SE = 5.293$), $\hat{\gamma}_1 = -0.411$ ($SE = .533$), $\hat{\gamma}_2 = -2.171$ ($SE = .995$), and $\hat{\gamma}_3 = 0.184$ ($SE = .101$). Two aspects of the complete-case analysis are worth highlighting. First, the interaction increased R^2 by .065 but was not statistically significant ($p = .087$). Given the strong reliance on null hypothesis significance tests in the behavioral sciences ([Cumming et al., 2007](#)), we suspect that most researchers would not attempt to probe the interaction. Second, excluding incomplete cases requires the missing com-

pletely at random (MCAR) assumption, whereby the probability of missing data is unrelated to the analysis variables. However, the data provide strong evidence against the MCAR assumption; a comparison of the incomplete and complete cases revealed that students with missing primary school reading scores have significantly lower test grades in middle school, $t(60) = 2.737, p = .008, d = 0.761$. A large body of literature suggests that complete-case estimates are prone to substantial bias when MCAR does not hold (for a review, see [Enders, 2010](#)), so there is good reason to view these estimates with caution.

Latent Variable Formulation for a Manifest Variable Regression

A brief review of the SEM specification for manifest variable regression provides the background for understanding a latent variable interaction model for missing data. To simplify the presentation, we consider a manifest variable regression model with two predictors, x and z (i.e., Equation 1 without the interaction term). To begin, a measurement model links each manifest variable to a corresponding latent variable, as follows:

$$\begin{aligned} x &= \tau_x + \lambda_x \xi_x + \delta_x \\ z &= \tau_z + \lambda_z \xi_z + \delta_z \\ y &= \tau_y + \lambda_y \eta_y + \varepsilon_y, \end{aligned} \quad (2)$$

where τ denotes a measurement intercept, λ is a factor loading, ξ_x and ξ_z are latent exogenous variables, η_y is the latent endogenous variable, and δ and ε are residuals. Software packages typically impose three identification constraints: (a) measurement intercepts set to zero, (b) factor loadings fixed to one, and (c) residuals held equal to zero. Collectively, these constraints define latent variables as exact duplicates of their manifest variable counterparts, such that the measurement models reduce to $\xi_x = x$, $\xi_z = z$, and $\eta_y = y$. Consequently, ξ and η are not latent variables in the conventional sense but are surrogates for the manifest variables.

A latent variable regression describes the associations among the manifest variables

$$\eta_y = \alpha + \gamma_1 \xi_x + \gamma_2 \xi_z + \zeta = \alpha + \xi \Gamma + \zeta, \quad (3)$$

where α is a regression intercept, γ_1 and γ_2 are regression coefficients for ξ_x and ξ_z , respectively, and ζ is a residual. In matrix form, ξ is an N by 2 matrix of latent variable scores, ξ_x and ξ_z , and Γ is a column vector containing the two regression slopes. The one-to-one linkage between the latent and manifest variables implies that the coefficients have the same interpretation as those from a standard regression model (e.g., γ_1 is the expected change in y for a one-unit increase in x , holding z constant). Consistent with standard regression models, the SEM that we consider in this article assumes that ζ follows a normal distribution with a zero mean and a residual variance ψ . The model also assumes that ξ_x and ξ_z (and thus x and z) are normally distributed with means κ_x and κ_z and a covariance matrix Φ . As we describe in the next section, this assumption is important for missing data handling.

The SEM mean structure provides a mechanism for "centering" latent exogenous variables without transforming the raw data. In the default parameterization, fixing the measurement intercept to zero defines ξ_x as a raw score, such that κ_x estimates the mean of x . Alternatively, constraining the latent mean to zero and estimat-

Table 1
Descriptive Statistics From the Reading Achievement Data
($N = 74$)

Variable	1	2	3
1. Primary school reading (x)	1.00		
2. Primary school learning problems (z)	-0.22	1.00	
3. Middle school reading (y)	0.77	-0.47	1.00
M	8.95	5.38	8.42
SD	1.78	1.16	1.64
% missing	67.57	1.35	16.22

ing the measurement intercept shifts the mean estimate to τ and defines ξ_x as a deviation score. Figure 1 shows the path diagrams of the two models. Notice that the models use different parameters to represent the means of x and z , but they are otherwise identical. Centering latent variables is a convenient strategy that we revisit with interaction models.

Maximum Likelihood Estimation With Missing Data

The maximum likelihood estimator in SEM programs uses a log likelihood function to quantify the discrepancy between the data and the model. Assuming a multivariate normal population distribution for the manifest variables, the sample log likelihood is

$$\log L = \sum_{i=1}^N -k_i - \frac{1}{2} \log |\Sigma_i(\theta)| - \frac{1}{2} [\mathbf{v}_i - \boldsymbol{\mu}_i(\theta)]' \Sigma_i^{-1}(\theta) \times [\mathbf{v}_i - \boldsymbol{\mu}_i(\theta)], \quad (4)$$

where k_i is a scaling factor that depends on the number of complete data points for case i , \mathbf{v}_i is the data vector for case i , and $\boldsymbol{\mu}_i(\theta)$ and $\Sigma_i(\theta)$ are the model-implied mean vector and covariance matrix, respectively. The key component of the log likelihood is a squared z -score (Mahalanobis distance) that quantifies the standardized difference between a participant's score vector and the corresponding model-implied means.

$$z_i^2 = [\mathbf{v}_i - \boldsymbol{\mu}_i(\theta)]' \Sigma_i^{-1}(\theta) [\mathbf{v}_i - \boldsymbol{\mu}_i(\theta)]. \quad (5)$$

The goal of estimation is to identify the parameter values that minimize the sum of the squared z -scores (and thus maximize the sample log likelihood). The i subscript allows the size and contents of the matrices to adjust across missing data patterns, such that z_i^2

depends only on the parameters that correspond to the observed data for a particular case.

To illustrate the missing data log likelihood function, reconsider the latent variable regression model from the top panel of Figure 1. The relevant matrices are as follows:

$$\mathbf{v}_i = \begin{bmatrix} y_i \\ x_i \\ z_i \end{bmatrix} \quad \boldsymbol{\mu}(\theta) = \begin{bmatrix} \alpha + \gamma_1 \kappa_x + \gamma_2 \kappa_z \\ \kappa_x \\ \kappa_z \end{bmatrix}$$

$$\Sigma(\theta) = \begin{bmatrix} \Gamma \Phi \Gamma' + \psi & \Gamma \Phi \\ \Phi \Gamma' & \Phi \end{bmatrix},$$

where $\Gamma \Phi \Gamma' + \psi$ is the model-implied variance of y , and Φ is the covariance matrix of x and z . The standardized distance measure for cases with missing y values depends only on the x and z parameters, as follows:

$$z_i^2 = \left[\begin{pmatrix} x_i \\ z_i \end{pmatrix} - \begin{pmatrix} \kappa_x \\ \kappa_z \end{pmatrix} \right]' \Phi^{-1} \left[\begin{pmatrix} x_i \\ z_i \end{pmatrix} - \begin{pmatrix} \kappa_x \\ \kappa_z \end{pmatrix} \right]$$

$$= \left[\begin{pmatrix} x_i \\ z_i \end{pmatrix} - \begin{pmatrix} \mu_x \\ \mu_z \end{pmatrix} \right]' \Sigma_{x,z}^{-1} \left[\begin{pmatrix} x_i \\ z_i \end{pmatrix} - \begin{pmatrix} \mu_x \\ \mu_z \end{pmatrix} \right].$$

Similarly, the z_i^2 values for cases with missing data on x and z depend only on the y parameters.

$$z_i^2 = [y_i - (\alpha + \gamma_1 \kappa_x + \gamma_2 \kappa_z)]' [\Gamma \Phi \Gamma' + \psi]^{-1} \times [y_i - (\alpha + \gamma_1 \kappa_x + \gamma_2 \kappa_z)] = \frac{(y_i - \mu_y)^2}{\sigma_y^2}.$$

Although it is not necessarily obvious from the previous equations, basing estimation on the observed data (as opposed to excluding incomplete data records) can improve the accuracy and precision of estimates and requires the more lenient MAR assumption.

An important feature of the SEM log likelihood is that all manifest variables function as outcomes, regardless of their role in the analysis. Returning to Figure 1, notice that ξ_x and ξ_z are the predictors, and x and z are dependent variables. As a consequence, the SEM estimator assumes that the manifest variables are multivariate normal. This is in contrast to ordinary least squares regression, where predictor variables are treated as fixed (i.e., no distributional assumptions). Although the SEM requires stricter distributional assumptions, multivariate normality is important for missing data handling because it is the mechanism by which the estimator “imputes” missing values during optimization. As a practical matter, assuming multivariate normality allows for incomplete predictors and outcomes.¹

A Latent Variable Interaction Model for Missing Data

The normality assumption is problematic for an interaction effect because the product of two random variables is nonnormal in shape (Craig, 1936; Lomnicki, 1967; Springer & Thompson,

¹ Note that the default parameterization in Mplus (Muthén & Muthén, 1998–2012) treats predictors as fixed. Specifying the variances and covariances among the predictors in the MODEL command invokes a normal distribution for the predictors.

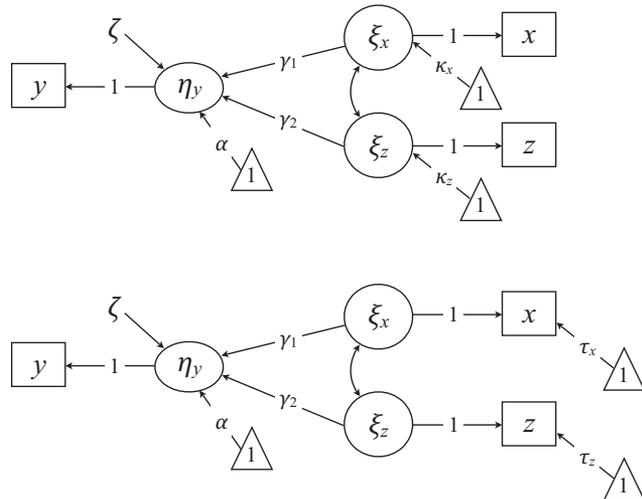


Figure 1. Two latent variable specifications for a manifest regression model. The triangles denote a unit vector, and the directional arrows originating from the triangles represent mean structure parameters (e.g., structural regression intercept, latent mean, or measurement intercept). Parameters constrained to zero (e.g., the δ and ϵ residuals) are omitted from the diagrams. The top diagram represents a model with the measurement intercepts constrained to zero, and the bottom diagram is a model with the latent means constrained to zero.

1966) and because the parameters of the x and z distributions determine the parameters of xz product (Aiken & West, 1991; Bohmstedt & Goldberger, 1969). Methodologists have developed approaches that use mixture distributions to model nonnormality from an interaction effect (e.g., latent moderated structural [LMS] equations; Kelava et al., 2011; Klein & Moosbrugger, 2000), but these models require at least two indicators per construct for identification. Consequently, we focus on three interaction models that use an incomplete product term as the sole indicator of a latent variable. These models are closely related to other product indicator models in the literature (e.g., Jöreskog & Yang, 1996; Kenny & Judd, 1984; Marsh et al., 2004, 2006), particularly that of Marsh et al. (2004).

To begin, a measurement model links each manifest variable to a corresponding latent variable. Equation 2 gives the measurement models for x , z , and y . We establish a measurement model for the xz product by multiplying the x and z equations, as follows:

$$\begin{aligned}xz &= (\tau_x + \lambda_x \xi_x + \delta_x)(\tau_z + \lambda_z \xi_z + \delta_z) \\ &= (\tau_x + \xi_x)(\tau_z + \xi_z) \\ &= \tau_x \tau_z + \tau_z \xi_x + \tau_x \xi_z + \xi_x \xi_z.\end{aligned}$$

Replacing the $\xi_x \xi_z$ product with a single latent variable and adding a residual term gives the measurement model for xz :

$$xz = \tau_x \tau_z + \tau_z \xi_x + \tau_x \xi_z + \xi_{xz} + \delta_{xz}. \quad (6)$$

Consistent with the lower order predictors, xz has a loading of one on its corresponding latent variable ξ_{xz} , and the residual is fixed at zero. The product variable requires three additional constraints: (a) the intercept is held equal to the product of the x and z intercepts, (b) the cross-loading of xz on ξ_x is set equal to τ_z , and (c) the cross-loading of xz on ξ_z is fixed at τ_x .

The structural regression is the same as Equation 1 but replaces manifest variables with latent variables, as follows:

$$\eta_y = \alpha + \gamma_1 \xi_x + \gamma_2 \xi_z + \gamma_3 \xi_{xz} + \zeta. \quad (7)$$

As before, the SEM assumes that ζ follows a normal distribution with a zero mean and a residual variance ψ . The model further assumes that the latent exogenous variables (and thus the manifest predictors) are normally distributed with a mean vector $\boldsymbol{\kappa} = [\kappa_x \kappa_z \kappa_{xz}]$ and a covariance matrix $\boldsymbol{\Phi}$. Again, the multivariate normality assumption is important for missing data handling.

The variance of a product variable is a complex function of the x and z parameters (Aiken & West, 1991; Bohmstedt & Goldberger, 1969). Rather than imposing complicated constraints on the elements in $\boldsymbol{\Phi}$, we follow Marsh et al.'s (2004) unconstrained approach by freely estimating the covariance matrix of the predictors. This approach has four important advantages. First, the resulting model is consistent with ordinary least squares regression in the sense that the partial regression coefficients condition on the sample estimates of the variances and covariances. Second, parameter estimates should be more robust to normality violations because the necessary constraints on $\boldsymbol{\Phi}$ assume that x and z have symmetric distributions (Aiken & West, 1991; Bohmstedt & Goldberger, 1969). Third, freely estimating the latent variable covariance matrix greatly simplifies model specification and computer syntax. Finally, freeing the parameters yields a saturated model that more closely aligns with the corresponding complete-data

analysis. A disadvantage of the unconstrained approach is the potential loss of power that occurs when x and z are normally distributed (Marsh et al., 2004). However, we feel that this disadvantage is trivial because manifest variables are often nonnormal.

Figure 2 shows a path diagram of the latent variable interaction model. As depicted, the model is not identified because it includes a measurement intercept and a latent mean for each predictor. We subsequently describe three parameterizations of the model that impose different identification constraints on the mean structure. These constraints determine the substantive interpretation of the lower order coefficients and provide a mechanism for estimating various conditional effects (i.e., simple slopes).

The Default Model

Recall from a previous section that the default specification for manifest variable regression constrains the measurement intercepts to zero and estimates the latent variable means. Fixing τ_x and τ_z to zero eliminates cross-loadings from the xz measurement model (see Equation 6), leading to the simplified path diagram in Figure 3. To highlight the free parameters, we omit parameters that are fixed at zero during estimation (i.e., cross-loadings, measurement intercepts, residuals). We henceforth refer to Figure 3 as the “default model” because SEM programs allow researchers to specify this analysis without explicitly defining latent variables or imposing parameter constraints.²

Latent Variable Analysis 1

To illustrate an interaction analysis with missing data, we fit the default model in Figure 3 to the reading achievement data. Appendix A of the online supplemental materials gives the Mplus syntax for the analysis, and the input file is available for download at www.appliedmissingdata.com/papers. It is important to emphasize the analysis includes all 74 cases and invokes the more lenient MAR assumption whereby observed scores in the analysis model determine missingness.

The left panel of Table 2 gives selected parameter estimates and standard errors from the analysis. Because the latent variables are exact duplicates of their manifest variable counterparts, the structural regression coefficients have the same meaning as those from an ordinary least squares regression with raw score predictors. For example, the regression intercept is the expected value of y (middle school reading achievement) when both predictors equal zero. Because the model includes an interaction, the lower order regression slopes are also conditional effects. For example, $\hat{\gamma}_1 = -.466$ is the conditional effect of x on y when z equals zero (i.e., the influence of primary school reading achievement for students with a zero score on the learning problems index), and $\hat{\gamma}_2 = -2.490$ is the conditional effect of z on y when x equals zero. The interaction effect ($\hat{\gamma}_3 = .212$) suggests that the association between x and y (primary and middle school reading scores, respectively) becomes more positive as z (learning problems) increases. Unlike the earlier complete-case analysis, the interaction was statistically significant ($p = .037$). This difference can be due to sampling variation, an increase in power, or a decrease in nonresponse bias (or a combi-

² Specifying the default model in Mplus requires only three lines of syntax: `x z xz; x z xz with x z xz; y on x z xz;`

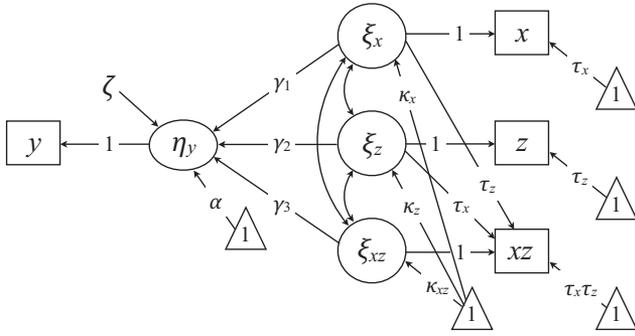


Figure 2. A latent variable interaction model. The triangles denote a unit vector, and the directional arrows originating from the triangles represent mean structure parameters (e.g., structural regression intercept, latent mean, or measurement intercept). Measurement model residuals are omitted from the diagram because these parameters are constrained to zero. As depicted, the model is not identified because it includes a measurement intercept and a latent mean for each predictor. The models that we describe in this article impose different mean structure constraints.

nation of the three). Although not shown in the table, the elements in κ are MAR-based estimates of the predictor variable means, and Φ contains the variances and covariances of the predictors. These parameters are not part of a standard regression model and result from assuming a normal distribution for the predictors.

Following a significant interaction, researchers typically examine the influence of the focal predictor and different values of the moderator. In this example, the lower order conditional effects are nonsensical because x and z cannot take on values of zero. Centering predictors prior to analysis (Aiken & West, 1991) or transforming estimates following the analysis (Bauer & Curran, 2005; Hayes & Matthes, 2009; Preacher et al., 2006) produce conditional effects that are interpretable within the range of the data. Because the default model does not provide a mechanism for centering latent variables, researchers would need to center the incomplete

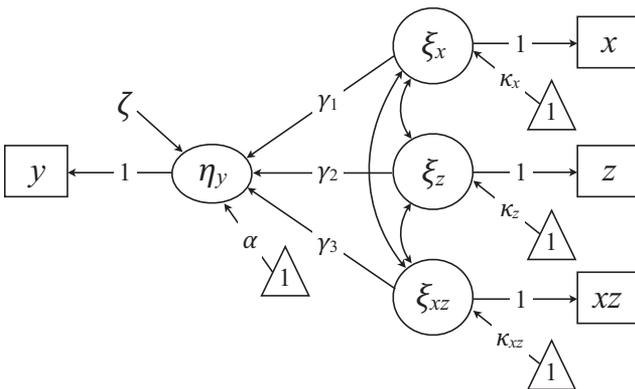


Figure 3. The default interaction model. The triangles denote a unit vector, and the directional arrows originating from the triangles represent mean structure parameters (e.g., regression intercept or latent means). The diagram omits all parameters that are fixed at zero during estimation (i.e., cross-loadings, measurement intercepts, residuals). Constraining the measurement intercepts eliminates cross-loadings, leading to a simplified model specification.

Table 2
Parameter Estimates From the Latent Variable Analyses

Effect	Default model		Free mean		Constrained mean	
	Estimate	SE	Estimate	SE	Estimate	SE
Intercept (α)	15.858	5.425	8.483	0.229	8.517	0.219
Primary school reading (γ_1)	-0.466	0.549	0.671	0.092	0.671	0.092
Primary school learning problems (γ_2)	-2.490	0.996	-0.596	0.158	-0.596	0.158
Interaction (γ_3)	0.212	0.101	0.212	0.101	0.212	0.101

predictors (e.g., at MAR-based mean estimates) prior to estimating the model.

Transforming estimates is convenient with the default model because specialized software tools for probing complete-data interactions effects (e.g., Preacher et al., 2006) can perform the necessary computations. The simple slope for the regression of y on x (the focal predictor), conditional on a particular value of z (the moderator) is

$$\hat{\beta}_1 = \hat{\gamma}_1 + \hat{\gamma}_3 z_c, \tag{8}$$

and the corresponding standard error is

$$SE_{\hat{\beta}_1} = \sqrt{\text{var}(\hat{\gamma}_1) + 2z_c \text{cov}(\hat{\gamma}_1, \hat{\gamma}_3) + z_c^2 \text{var}(\hat{\gamma}_3)}, \tag{9}$$

where z_c is the target value of the moderator, and $\text{var}(\bullet)$ and $\text{cov}(\bullet)$ are elements from the parameter covariance matrix. Referencing the ratio of the simple slope to its standard error (i.e., a z statistic) to a standard normal distribution gives a significance test for the conditional effect.

To illustrate the transformation procedure, consider the conditional effect of x on y at the mean of z (i.e., the influence of primary school reading for a student with average learning problems). Substituting the appropriate coefficients and the mean of z into Equation 8 gives the simple slope:

$$\hat{\beta}_1 = \hat{\gamma}_1 + \hat{\gamma}_3 \hat{\kappa}_z = -.466 + .212(5.375) = .671.$$

As a second example, consider the conditional effect of x on y at one standard deviation above the mean of z (i.e., the influence of primary school reading for a student with substantial learning problems). The simple slope is

$$\begin{aligned} \hat{\beta}_1 &= \hat{\gamma}_1 + \hat{\gamma}_3 (\hat{\kappa}_z + \sqrt{\hat{\phi}_{\xi_z}}) = -.466 + .212(5.375 + \sqrt{1.339}) \\ &= .916, \end{aligned}$$

where the terms in parentheses define a score value at one standard deviation above the mean (the square root of $\hat{\phi}_{\xi_z}$ is an MAR-based estimate of the z standard deviation). As a final example, the simple slope of x on y at one standard deviation below the mean of z is

$$\begin{aligned} \hat{\beta}_1 &= \hat{\gamma}_1 + \hat{\gamma}_3 (\hat{\kappa}_z - \sqrt{\hat{\phi}_{\xi_z}}) = -.466 + .212(5.375 - \sqrt{1.339}) \\ &= .426. \end{aligned}$$

The Mplus program in the online supplemental materials uses the MODEL CONSTRAINT command to compute the conditional

effects and their standard errors, and specialized software tools for probing complete-data interactions effects can also perform these computations (see Preacher et al., 2006).

Interaction Models With Centered Latent Variables

Recall from an earlier section that constraining the latent means to zero and estimating the measurement intercepts defines latent variables as deviation scores, effectively “centering” the exogenous variables. Centering latent variables is convenient because it requires little effort and yields lower order effects that are interpretable within the range of the data. Moreover, the centered model provides a mechanism for estimating and testing conditional effects without the need for transformations.

For the lower order latent variables, constraining κ_x and κ_z to zero shifts the predictor means to the intercepts and defines ξ_x and ξ_z as deviation scores. Estimating τ_x and τ_z activates two cross-loadings in the xz measurement model (see Equation 6) and requires three additional constraints: (a) the influence of ξ_x on xz is set equal to τ_z , (b) the influence of ξ_z on xz is set equal to τ_x , and (c) the xz measurement intercept is fixed at the product of τ_x and τ_z . Centering ξ_{xz} is inappropriate because the mean of a product variable does not equal zero, even when the x and z means are zero. Bohmstedt and Goldberger (1969) have shown that the expected value (i.e., mean) of a product variable equals the covariance between x and z plus the product of the x and z means, as follows:

$$E(xz) = \text{cov}(x, z) + E(x)E(z) = \sigma_{xz} + \mu_x\mu_z. \quad (10)$$

Because the xz measurement intercept absorbs the product of the x and z means, Equation 10 implies that κ_{xz} should equal the covariance between x and z . Although constraining the latent mean would simplify the model, estimating κ_{xz} maintains consistency with a complete-data regression analysis in the sense that the latent variable model perfectly reproduces the sample moments. Note that κ_{xz} will not necessarily equal the covariance between ξ_x and ξ_z because the model treats κ_{xz} and $\varphi_{\xi_x\xi_z}$ as a unique parameters.

Figure 4 shows a path diagram of the interaction model with ξ_x and ξ_z in deviation score format. To highlight the free parameters, we omit parameters that are fixed at zero during estimation. We henceforth refer to Figure 4 as the “free mean model” because it treats κ_{xz} as a free parameter during estimation. Note that default and free mean models are equivalent parameterizations of the general model from Figure 2. The following algebraic transformations relate the parameters from the two models:

$$\begin{aligned} \kappa_x^{(D)} &= \tau_x^{(FM)} \\ \kappa_z^{(D)} &= \tau_z^{(FM)} \\ \kappa_{xz}^{(D)} &= \tau_x^{(FM)}\tau_z^{(FM)} + \kappa_{xz}^{(FM)} \\ \gamma_0^{(D)} &= \gamma_0^{(FM)} + \gamma_1^{(FM)}\tau_x^{(FM)} + \gamma_2^{(FM)}\tau_z^{(FM)} + \gamma_3^{(FM)}\tau_x^{(FM)}\tau_z^{(FM)} \\ \gamma_1^{(D)} &= \gamma_1^{(FM)} + \gamma_3^{(FM)}\tau_z^{(FM)} \\ \gamma_2^{(D)} &= \gamma_2^{(FM)} + \gamma_3^{(FM)}\tau_x^{(FM)} \\ \gamma_3^{(D)} &= \gamma_3^{(FM)} \\ \psi^{(D)} &= \psi^{(FM)} \\ \Phi^{(D)} &= \Phi^{(FM)} \end{aligned}$$

where the (D) and (FM) superscripts denote the default and free mean models, respectively.

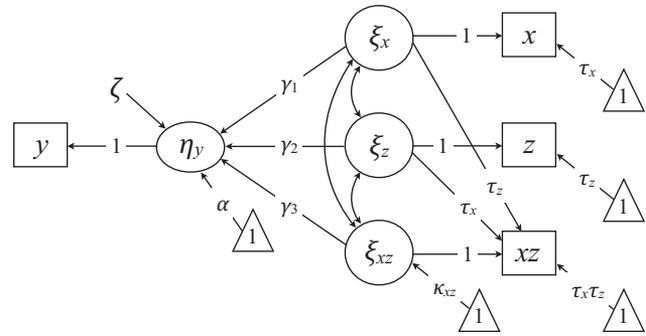


Figure 4. The free mean interaction model. The triangles denote a unit vector, and the directional arrows originating from the triangles represent mean structure parameters (e.g., regression intercept or latent means). The diagram omits all parameters that are fixed at zero during estimation (i.e., cross-loadings, measurement intercepts, residuals). The model estimates the κ_{xz} latent mean and constrains the xz measurement intercept equal to the product of τ_x and τ_z .

Latent Variable Analysis 2

To illustrate an analysis with centered latent variables, we fit the free mean model in Figure 4 to the reading achievement data. Appendix B of the online supplemental materials gives the Mplus syntax for the analysis, and the input file is available for download at www.appliedmissingdata.com/papers. The middle panel of Table 2 gives selected parameter estimates and standard errors from the analysis. Because ξ_x and ξ_z are deviation scores, the structural regression coefficients have the same meaning as those from an ordinary least squares regression with centered predictors. For example, $\hat{\gamma}_1 = .671$ is the conditional effect of x on y when z is at the mean (i.e., the influence of primary school reading for a student with average learning problems). Similarly, $\hat{\gamma}_2 = -.596$ is the conditional effect of z on y when x is at its mean. Finally, the interaction effect ($\hat{\gamma}_3 = .212$) suggests that the association between x and y (primary and middle school reading scores, respectively) becomes more positive as z (learning problems) increases. Again, note that the interaction effect is statistically significant ($p = .037$).

The free mean model yields lower order coefficients that are interpretable within the range of the data, and the transformations in Equations 8 and 9 can generate additional conditional effects. For example, the simple slope of x on y at one standard deviation above the mean of z (i.e., the influence of primary school reading for a student with substantial learning problems) is as follows:

$$\hat{\beta}_1 = \hat{\gamma}_1 + \hat{\gamma}_3(\kappa_z + \sqrt{\hat{\phi}_{\xi_z}}) = .671 + .212(0 + \sqrt{1.339}) = .916.$$

Similarly, the conditional effect of x on y at one standard deviation below the mean of z is

$$\hat{\beta}_1 = \hat{\gamma}_1 + \hat{\gamma}_3(\kappa_z - \sqrt{\hat{\phi}_{\xi_z}}) = .671 + .212(0 - \sqrt{1.339}) = .426.$$

Notice that these estimates are identical to the transformed estimates from the default model. This result is expected because the two models are equivalent (i.e., an algebraic transformation relates the two sets of parameters).

The literature recommends using meaningful values of z_c (e.g., a diagnostic cutoff, the mean of a normative group) to probe

interaction effects whenever possible (Cohen, Cohen, West, & Aiken, 2003, p. 269; West, Aiken, Wu, & Taylor, 2007). Because the free mean model expresses the latent predictors in deviation score format, the target value of z_c should be a deviation score. A slight modification to Equation 8 gives the appropriate transformation

$$\hat{\beta}_1 = \hat{\gamma}_1 + \hat{\gamma}_3(z_c - \hat{\tau}_z), \quad (11)$$

where $\hat{\tau}_z$ is an MAR-based estimate of the z mean.

The Constrained Mean Model

The final latent variable model reverses the constraint on the xz mean structure by freely estimating the measurement intercept and constraining the latent mean equal to the covariance between ξ_x and ξ_z . (i.e., $\kappa_{xz} = \phi_{\xi_x \xi_z}$). Under this setup, the xz measurement model becomes

$$xz = \tau_{xz} + \tau_z \xi_x + \tau_x \xi_z + \xi_{xz} + \delta_{xz}, \quad (12)$$

where τ_{xz} is a free intercept parameter. We henceforth refer to this as the *constrained mean model* because κ_{xz} is now a fixed parameter. Figure 5 shows a path diagram of the model. The free mean and constrained mean models are identical in the sense that they (a) generate the same model-implied mean vector and covariance matrix, (b) perfectly reproduce the sample moments, and (c) produce estimates with the same substantive interpretation. However, the two models do not necessarily produce the same parameter estimates.

Latent Variable Analysis 3

We fit the constrained mean model in Figure 5 to the reading achievement data. Appendix C of the online supplemental materials gives the Mplus syntax for the analysis, and the input file is available for download at www.appliedmissingdata.com/papers. The right panel of Table 2 gives selected parameter estimates and standard errors from the analysis. As seen in the table, the free mean and constrained mean models produced identical regression

slopes but slightly different intercept coefficients ($\hat{\alpha} = 8.517$ vs. $\hat{\alpha} = 8.483$). This disparity owes to differences in the latent mean estimates; the free mean model produced $\hat{\kappa}_{xz} = -.292$, whereas the constrained mean model produced $\hat{\kappa}_{xz} = \hat{\phi}_{\xi_x \xi_z} = -.453$. Despite the numeric differences, the two models produce identical substantive interpretations, and the process of estimating simple slopes is the same. The syntax in Appendix C of the online supplemental materials includes code to estimate the simple effect of x at one standard deviation above and below the z mean.

An Alternate Approach to Probing Interaction Effects

Throughout the analysis examples we used the transformation in Equations 8 and 9 to estimate and test simple slopes. This option is convenient with Mplus because the MODEL CONSTRAINT command can define simple slopes as additional parameters, the values of which are determined by the interaction model parameters. However, not all SEM software packages offer this functionality. Although specialized web-based software tools (Preacher et al., 2006) can also perform these computations, culling the necessary information from the computer output can be time-consuming and error-prone.

Following the centering-based approach to estimating simple slopes (Aiken & West, 1991), constraining κ_z (and possibly κ_x) to values other than zero provides a mechanism for estimating and testing conditional effects. For example, constraining κ_z to negative one times the square root of ϕ_{ξ_z} centers ξ_z at a value one standard deviation above the z mean, giving a γ_1 coefficient that estimates the conditional effect of x on y at a high value of z . Similarly, constraining κ_z to the square root of ϕ_{ξ_z} centers ξ_z at one standard deviation below the z mean, such that γ_1 estimates the simple slope of x for a low value of z . This method is flexible and can be implementing in any commercial SEM program. Appendix D of the online supplemental materials provides additional details on this approach.

Multiple Imputation

Multiple imputation is a second MAR-based procedure for treating incomplete interaction effects. Multiple imputation consists of three steps: an imputation phase, an analysis phase, and a pooling phase. The imputation phase generates multiple copies of the data set, each of which contains unique estimates of the missing values. This phase typically employs an iterative algorithm (e.g., data augmentation; Schafer, 1997) that repeatedly cycles between an imputation step (I-step) and a posterior step (P-step). The I-step uses a regression model to draw imputations from a multivariate normal distribution, and the subsequent P-step draws a new covariance matrix and mean vector from a distribution of plausible parameter values (i.e., a posterior distribution). These parameter values carry forward to the next I-step where they are the building blocks for a new regression model and new imputations. In the analysis phase, researchers use standard software to analyze each imputed data set, and the subsequent pooling phase combines the estimates and standard errors into a single set of results. Many popular software programs now provide facilities that automate this process.

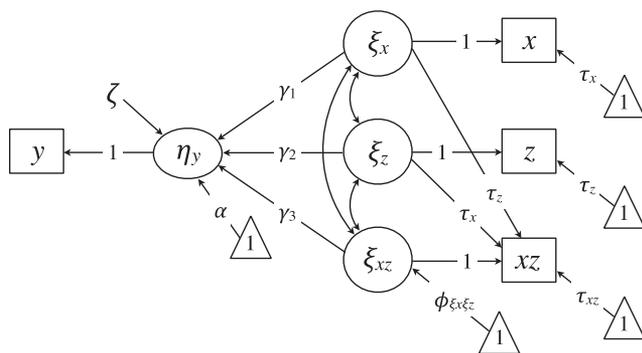


Figure 5. The constrained mean model. The triangles denote a unit vector, and the directional arrows originating from the triangles represent mean structure parameters (e.g., regression intercept or latent means). The diagram omits all parameters that are fixed at zero during estimation (i.e., cross-loadings, measurement intercepts, residuals). The model estimates the xz measurement intercept and constrains the κ_{xz} latent mean to the covariance between x and z (i.e., $\kappa_{xz} = \phi_{\xi_x \xi_z}$).

Imputing Product Terms

Product terms add complexity to imputation-based missing data handling. For one, the imputation phase must incorporate the interaction effect or its subsequent estimate will be biased toward zero (Enders, 2010; Enders & Gottschall, 2011; Graham, 2009; Schafer, 1997). von Hippel (2009) investigated three possible approaches to imputing an incomplete interaction term. The impute-then-transform method fills in x , z , and y and subsequently computes the xz product from the imputed x and z values. Executing the imputation phase without the interaction attenuates the resulting point estimate because the imputations are consistent with an additive model that includes only lower order effects. The so-called passive imputation method includes xz in the imputation process but subsequently replaces it with the product of the imputed x and z values prior to analysis. Passive imputation is a variation of impute-then-transform and produces similar biases. Finally, the transform-then-impute method includes xz in the imputation process and uses the filled-in product term in the subsequent analysis phase. Because the xz imputations are drawn from a normal distribution with a unique mean and variance, the imputed values do not equal the product of the x and z imputations. Nevertheless, von Hippel showed that transform-then-impute is the only method capable of reproducing the population parameters. Consequently, we focus on this approach for the remainder of the article, and we extend von Hippel's work by outlining centering procedures and methods for probing interactive effects with multiply imputed data.

Consistent with maximum likelihood estimation, multiple imputation requires distributional assumptions for the incomplete variables, typically multivariate normality. As noted previously, product variables are at odds with this assumption. To illustrate the issue, consider the I-step for a case with missing values on x and xz . Using the covariance matrix and mean vector from the preceding P-step, the imputation algorithm estimates a regression model where z and y (the complete variables) predict x and xz (the incomplete variables). The regression parameters define a bivariate normal distribution of plausible replacement scores that is centered at a pair of predicted values and has a covariance matrix equal to the residual covariance matrix from the regression analysis. More formally, the imputations at I-step ($t + 1$) are drawn from the following probability distribution:

$$p(x_{(mis)}^{(t+1)}, xz_{(mis)}^{(t+1)} | y, z, \theta^{(t)}) \sim N(\mathbf{X}\beta^{(t)}, \Sigma_{x,xz|y,z}^{(t)}), \quad (13)$$

where $x_{(mis)}^{(t+1)}$ and $xz_{(mis)}^{(t+1)}$ represent the imputations, $\theta^{(t)}$ denotes the parameters from the preceding P-step, $\sim N$ is the bivariate normal distribution, \mathbf{X} contains the complete predictors (z , y , and a unit vector for the intercept), $\beta^{(t)}$ is a matrix of regression coefficients, and $\Sigma_{x,xz|y,z}^{(t)}$ is the residual covariance matrix. Drawing imputations from Equation 13 is potentially problematic because a product variable is nonnormal in shape and because the regression parameters do not explicitly model the deterministic features of the xz distribution. Whether these issues pose a problem for the resulting parameter estimates is an open question that we investigate later in the article.

Multiple Imputation Analysis 1

To illustrate a multiple imputation analysis, we applied Schafer's (1997) data augmentation algorithm to the reading achievement data. To begin, we used the MI procedure in SAS to generate 50 imputed data sets. Following the transform-then-impute approach (von Hippel, 2009), the imputation phase included the product of primary school reading scores and learning problems ratings. Although researchers often center predictors prior to computing the product term, we used raw score variables for the analysis. After generating the imputations, we used the REG procedure to fit the model from Equation 1 to each data set, and we subsequently used the MIANALYZE procedure to pool the estimates and standard errors. Appendix E of the online supplemental materials gives the SAS syntax for the analysis, and the input file is available for download at www.appliedmissingdata.com/papers.

The left panel of Table 3 gives selected parameter estimates and standard errors from the analysis. Because imputation is on the raw score metric, the regression coefficients have the same meaning as those from an ordinary least squares regression with raw score predictors. For example, $\hat{\gamma}_1 = -.569$ is the conditional effect of x on y when z equals zero (i.e., the influence of primary school reading scores for students with a zero score on the learning problems index), and $\hat{\gamma}_2 = -2.615$ is the conditional effect of z on y when x equals zero. The interaction effect ($\hat{\gamma}_3 = .223$) suggests that the association between x and y (primary and middle school reading scores, respectively) becomes more positive as z (learning problems) increases. Unlike the earlier complete-case analysis, the interaction was statistically significant ($p = .025$). This difference owes to an increase in power, a decrease in nonresponse bias, or both.

Consistent with the latent variable model, researchers can use centering or transformations to probe the interaction effect. We describe the transformation procedure here and take up centering in the next section. Following Rubin's (1987) pooling rules, the multiple imputation estimate of a simple slope is the arithmetic average of the conditional effects from the m data sets, as follows:

$$\hat{\beta}_1 = \frac{1}{m} \sum_{i=1}^m (\hat{\gamma}_1^{(i)} + \hat{\gamma}_3^{(i)} z_c^{(i)}). \quad (14)$$

We omit the pooling equations for the standard error because we anticipate that most researchers will not perform the computations by hand.

Table 3
Parameter Estimates From the Multiple Imputation Analyses

Effect	Raw score		Free mean		Constrained mean	
	Estimate	SE	Estimate	SE	Estimate	SE
Intercept (α)	16.942	5.069	8.498	0.158	8.519	0.135
Primary school reading (γ_1)	-0.569	0.503	0.630	0.105	0.630	0.105
Primary school learning problems (γ_2)	-2.615	0.922	-0.623	0.163	-0.623	0.163
Interaction (γ_3)	0.223	0.092	0.223	0.092	0.223	0.092

To illustrate the transformation procedure, we computed the conditional effect of x on y at the mean of z (i.e., the influence of primary school reading for a student with average learning problems). Substituting the appropriate coefficients and the mean of z into Equation 14 gives the simple slope:

$$\hat{\beta}_1 = \frac{1}{m} \sum_{i=1}^m (\hat{\gamma}_1^{(i)} + \hat{\gamma}_3^{(i)} \hat{\mu}_z^{(i)}) = .630.$$

As a second example, consider the conditional effect of x on y at one standard deviation above the mean of z (i.e., the influence of primary school reading for a student with substantial learning problems). The simple slope is

$$\hat{\beta}_1 = \frac{1}{m} \sum_{i=1}^m (\hat{\gamma}_1^{(i)} + \hat{\gamma}_3^{(i)} [\hat{\mu}_z^{(i)} + \hat{\sigma}_z^{(i)}]) = .890.$$

Finally, the simple slope at one standard deviation below the mean is

$$\hat{\beta}_1 = \frac{1}{m} \sum_{i=1}^m (\hat{\gamma}_1^{(i)} + \hat{\gamma}_3^{(i)} [\hat{\mu}_z^{(i)} - \hat{\sigma}_z^{(i)}]) = .370.$$

Note that these estimates are quite similar to those from the latent variable analyses.

Post-Imputation Centering

The transformation approach to probing an interaction effect is difficult to implement without flexible pooling software (e.g., the SPSS pooling facility does not accommodate the procedure). In a complete-data analysis, centering provides an alternate mechanism for implementing the pick-a-point approach to estimating simple slopes (Aiken & West, 1991). For example, if a researcher wants to compute the simple slope of y on x at z_c , the steps are as follows: (a) center z at z_c , (b) compute the xz product term, and (c) estimate the regression model. This process defines γ_1 as the conditional influence of x on y at z_c . Because the imputation phase must include the product variable, performing steps (a) and (b) prior to imputation is a natural choice. This sequence works well when z_c does not depend on the data (e.g., z_c is a clinically meaningful score value).

In the absence of meaningful cutoffs, researchers often examine conditional effects at different points in the z distribution. In this situation, centering prior to imputation is unwieldy because it requires new imputations for each simple slope. To avoid this problem, we developed a post-imputation centering approach that consists of the following steps: (a) compute the xz product by multiplying the raw x and z variables, (b) perform imputation, (c) rescale the predictor variables and the product term to deviation score format, (d) estimate the regression model, and (e) pool the estimates and standard errors. This procedure can generate any number of conditional effects from a single collection of imputed data sets. Further, the procedure is easy to implement in general-use software packages such as SPSS and SAS. The remainder of this section describes the rescaling procedure for step (c).

The centering expressions for lower order predictors are

$$\begin{aligned} x_{\text{dev}}^{(i)} &= x^{(i)} - x_c^{(i)} \\ z_{\text{dev}}^{(i)} &= z^{(i)} - z_c^{(i)}, \end{aligned} \tag{15}$$

where $x_{\text{dev}}^{(i)}$ and $z_{\text{dev}}^{(i)}$ are the centered variables from data set i , $x^{(i)}$ and $z^{(i)}$ are the corresponding raw scores, and $x_c^{(i)}$ and $z_c^{(i)}$ are the centering constants that correspond to the desired conditional effects. The centering expression for the interaction is based on the algebraic expansion of the product of two deviation scores

$$\begin{aligned} xz_{\text{dev}} &= (x - x_c)(z - z_c) \\ &= xz - xz_c - zc + x_c z_c \\ &= xz - [xz_c + zc - x_c z_c], \end{aligned}$$

where subtracting the collection of terms in brackets converts the raw score product to a metric that is consistent the lower order predictors. Applying this idea to multiple imputation gives the following centering expression the product variable:

$$xz_{\text{dev}}^{(i)} = xz^{(i)} - x^{(i)}z_c^{(i)} - z^{(i)}x_c^{(i)} + x_c^{(i)}z_c^{(i)}. \tag{16}$$

It is important to emphasize that $xz_{\text{dev}}^{(i)}$ is the imputed product term rather than the product of the imputed x and z variables.

Multiple Imputation Analysis 2

To illustrate post-imputation centering, we reanalyzed the imputed data sets from the previous analysis example. To provide a comparison to the centered latent variable models, we began by using Equations 15 and 16 to rescale the imputations to a centered solution where x and z are deviations from the mean (i.e., $x_c^{(i)} = \hat{\mu}_x^{(i)}$ and $z_c^{(i)} = \hat{\mu}_z^{(i)}$). Appendix F of the online supplemental materials gives the SAS and SPSS syntax for the analysis, and the input files are available at www.appliedmissingdata.com/papers.

The middle panel of Table 3 gives selected parameter estimates and standard errors from the analysis. The regression coefficients have the same meaning as those from an ordinary least squares regression with centered predictors. For example, $\hat{\gamma}_1 = .630$ is the conditional effect of x on y when z is at the mean (i.e., the influence of primary school reading for a student with average learning problems), and $\hat{\gamma}_2 = -.623$ is the conditional effect of z on y when x is at its mean. Finally, the interaction effect ($\hat{\gamma}_3 = .223$) suggests that the association between x and y (elementary and high school reading scores, respectively) becomes more positive as z (learning problems) increases.

Next, we rescaled the predictors to obtain the conditional effect of x on y at one standard deviation above mean of z (i.e., the influence of primary school reading for a student with substantial learning problems). To estimate this simple slope, we used $z_c^{(i)} = \hat{\mu}_z^{(i)} + \hat{\sigma}_z^{(i)}$ to rescale z and xz and reanalyzed the data. The resulting estimate was $\hat{\gamma}_1 = .890$. Finally, repeating this process using $z_c^{(i)} = \hat{\mu}_z^{(i)} - \hat{\sigma}_z^{(i)}$ gives the simple slope at one standard deviation below the mean of z , the estimate of which was $\hat{\gamma}_1 = .370$. Notice that post-imputation centering and transformation (Equation 14) produced identical estimates of the conditional effects (standard errors were also the same). At an intuitive level, the two procedures should be equivalent because the use the same imputations and the same values of $x_c^{(i)}$ and $z_c^{(i)}$. Recall that, in the

latent variable framework, the default and free mean models were similarly equivalent.

Constrained Mean Centering

In the SEM framework, we described two centered models that use a latent variable (ξ_{xz}) to represent the deviation score version of xz . In the context of multiple imputation, each $xz_{\text{dev}}^{(i)}$ is essentially a different realization of ξ_{xz} , and the mean of $xz_{\text{dev}}^{(i)}$ is analogous to the κ_{xz} latent mean from the centered models. These linkages suggest a modification to post-imputation centering that parallels the difference between the free mean and constrained mean latent variable models.

Returning to Equation 10, notice that the expected value (i.e., mean) of a deviation score product equals the covariance between x and z . In the latent variable framework, the κ_{xz} latent mean can be freely estimated (the free mean model) or held equal to this covariance (the constrained mean model). The centering expression from Equation 16 is consistent with free mean model in the sense that $\mu_{xz_{\text{dev}}}^{(i)}$ is not constrained to a particular value and captures the portion of the xz mean that remains after subtracting out the product of the x and z means. For this reason, we henceforth refer to Equation 16 as *free mean centering*. We modified post-imputation centering by subtracting the estimate of the product variable mean and replacing it with the components of the expected value expression in Equation 10, as follows:

$$xz_{\text{dev}}^{(i)} = xz^{(i)} \left[-\hat{\mu}_{xz}^{(i)} + \hat{\sigma}_{xz}^{(i)} + \hat{\mu}_x^{(i)} \hat{\mu}_z^{(i)} \right] - x^{(i)} z_c^{(i)} - z^{(i)} x_c^{(i)} + x_c^{(i)} z_c^{(i)}. \quad (17)$$

Although not obvious from the equation, the bracketed terms implement a “constraint” that forces $\mu_{xz_{\text{dev}}}^{(i)}$ equal to the covariance between x and z in data set i . In line with our previous terminology, we henceforth refer to Equation 17 as *constrained mean centering*.

Multiple Imputation Analysis 3

To illustrate constrained mean centering, we reanalyzed the imputed data sets from the previous analysis examples. To provide a comparison to the previous analyses, we used Equations 15 and 17 to rescale the imputations to a centered solution where x and z are deviations from the mean (i.e., $x_c^{(i)} = \hat{\mu}_x^{(i)}$ and $z_c^{(i)} = \hat{\mu}_z^{(i)}$). Appendix G of the online supplemental materials gives the SAS and SPSS syntax for the analysis, and the input files are available at www.appliedmissingdata.com/papers. As seen in right panel of Table 3, free mean and constrained mean centering produced identical regression slopes but slightly different intercept coefficients ($\hat{\alpha} = 8.519$ vs. $\hat{\alpha} = 8.498$). This disparity owes to the fact that the analyses produced different estimates of the product term mean; free mean centering produced $\hat{\mu}_{xz_{\text{dev}}} = -.311$, whereas the constrained mean estimate was $\hat{\mu}_{xz_{\text{dev}}} = \hat{\sigma}_{xz} = -.424$. Despite these numeric differences, the choice of centering approach does not affect the substantive interpretation of the estimates, and it does not alter the process of probing simple slopes. Appendix G of the online supplemental materials includes code to estimate the simple effect of x at one standard deviation above and below the z mean.

Simulation Studies

We used Monte Carlo computer simulations to evaluate the performance of the maximum likelihood estimation and multiple imputation. Although there is no reason to expect differences between the two approaches, we know of no published simulations that have investigated the issue of incomplete interactive effects. Previous research suggests that MAR-based methods can yield consistent estimates when normality is violated (e.g., Demirtas et al., 2008; Enders, 2001; Savalei & Bentler, 2005; Yuan, 2009; Yuan & Bentler, 2010; Yuan & Zhang, 2012), but it is unclear whether this finding extends to interactions. Further, von Hippel’s (2009) analytic work has limited generalizability because it examined imputation from a known (rather than estimated) population covariance matrix. The simulation syntax is available upon request.

The regression model from Equation 1 served as the data-generating population model for the simulations. Because we did not expect the manipulated factors to exert complicated non-linear effects, we chose to minimize the complexity of the design while still examining a range of conditions that encompasses the variety of substantive research applications. Specifically, we introduced three distribution shapes for x and z (normal, kurtotic, skewed and kurtotic), three interaction effect size values (zero, small, and large increment in R^2), four sample size conditions (N s between 50 and 5,000), two missing data mechanisms (MCAR and MAR), and four missing data handling methods (the free and constrained mean latent variable models, and multiple imputation with free and constrained mean centering). Note that we chose not to manipulate the missing data rate because this factor tends to produce predictable and uninteresting findings (e.g., as the missing data rate increases, so do the negative consequences of missing data). Rather, we imposed a constant 20% missing data rate on one of the predictors (and thus the interaction). We chose this rather extreme value because we felt that it would clearly expose any problems with the missing data handling approaches. The remainder of this section describes the simulation conditions in more detail.

Sample Size

We implemented four sample size conditions, $N = 50, 200, 400$, and 5,000. In Jaccard and Wan’s (1995) review of published multiple regression applications, the 75th percentile of the sample size distribution was approximately 400, and the median value was roughly 175. Consequently, we believe that our sample size conditions are fairly representative of published research studies, particularly in the field of psychology. We implemented the $N = 5,000$ condition to study the large-sample properties of the missing data methods.

Distribution Shape

Because behavioral science data rarely satisfy multivariate normality (Micceri, 1989), we varied the distribution of the lower order predictors. We opted to investigate three distributional conditions (normal, kurtotic-only, skewed and kurtotic). In the normal distribution condition, both x and z had skewness and excess kurtosis values of zero. The kurtosis-only condition had skewness and kurtosis values equal to 0 and 4, respectively, and the skewed

condition had skewness and kurtosis values of 2 and 6, respectively. Previous simulation studies have characterized the latter values as relatively extreme (Curran, West, & Finch, 1996). We used Fleishman's power method (Fleishman, 1978; Vale & Mauriello, 1983) to impose the desired distribution shapes for x and z . The power method tends to produce skewness and kurtosis estimates that are less extreme than the target values, particularly at smaller sample sizes. Our simulation checks indicated that skewness and kurtosis estimates were substantially lower than the target values in the $N = 50$ condition and improved as sample size increased. This trend is consistent with our previous experiences with this approach (e.g., Enders, 2001).

Population Parameters and Data Generation

Table 4 summarizes the data generation parameters. For all simulations, we arbitrarily set the predictor means to $\mu_x = 12$ and $\mu_z = 25$, respectively, and we fixed the predictor variances to $\sigma_x^2 = \sigma_z^2 = 4$. For simplicity, we fixed the correlation between x and z at $\rho_{x,z} = .30$, corresponding with Cohen's definition of a medium effect size (Cohen, 1988). Again, we did not manipulate the mean and the variance of the product term because x and z determine these parameters.

Because the interaction effect was our primary focus, we implemented three effect size increments for this variable ($R_{\Delta}^2 = 0, .01, \text{ and } .05$). To begin, we arbitrarily chose to have the lower order terms explain 30% of the variance when the interaction term was omitted from the model. For simplicity, we imposed equality constraints on the lower order regression slopes, such that $\gamma_1 = \gamma_2 = 5$. We arbitrarily set the intercept coefficient to the same value. For the non-zero effect size conditions, we specified a γ_3 coefficient and a residual variance that incremented the total R^2 by either .01 or .05. Chaplin (1991) reviewed the literature and found that interactions in field studies typically account for one to three percent of the variance in the outcome. Thus, $R_{\Delta}^2 = .01$ represents a relatively small interaction effect, and $R_{\Delta}^2 = .05$ represents a large effect. Methodological reviews also suggest that the total R^2 values from our simulations are representative of interaction effects from published research studies (Jaccard & Wan, 1995).

Our method for deriving the population value for the interaction coefficient warrants a brief discussion. As explained previously, the x and z distributions determine the distribution of the product. When x and z are symmetrically distributed (as in the normal and the kurtosis-only conditions), well-known expressions define the covariance between x (or z) and the xz product (Aiken & West, 1991, pp. 180–181; Bohrnstedt & Goldberger, 1969). Conse-

quently, the value of γ_3 is fully determined after specifying the effect size and the other regression model parameters. However, when one or both of the component distributions is asymmetric (e.g., the nonnormal condition with non-zero skewness), it is no longer possible to analytically derive γ_3 because the covariances between the lower order terms and the product term are a complex function of skewness. Consequently, we implemented a simulation that iteratively auditioned values for the interaction coefficient in the skewed condition ($N = 1,000,000$ in each artificial data set). We saved the coefficients and the R^2 values from this simulation and subsequently chose the γ_3 value that produced the desired increment in R^2 .

After specifying the population parameters, we used the IML procedure in SAS 9.2 (SAS Institute, 2008) to generate 2,000 artificial data sets within each between-subjects design cell. The data generation procedure utilized the following steps. First, we generated the predictor variable scores from a standard normal distribution with a mean of zero and a variance of one. Second, we imposed the desired variances and covariance on x and z . Third, we used the Fleishman's (1978) power method to introduce skewness and kurtosis. Fourth, we generated the interaction term by multiplying x and z . Fifth, we generated a vector of residual terms from a normal distribution with a mean of zero and a variance equal to the residual variance from the population regression model. Sixth, we generated the y values by substituting the variables from previous steps into the population regression model. The preceding steps produced artificial data sets with predictors in deviation score format. In the final step, we imposed a mean structure by adding the desired means to x and z and recomputing the interaction term.

Missing Data Mechanisms

We implemented two missing data mechanisms: MCAR and MAR. In the MCAR condition, we generated a vector of uniform random numbers and subsequently deleted x (and thus xz) scores for cases in the lower quintile of the random number distribution. In the MAR condition, the probability of missing data was related to the values of z . We first divided the z distribution into quintiles and then used a uniform random number to randomly delete 75% of the x values from within the first (i.e., lowest) z quintile, 15% of the x values from within the second z quintile, and 10% of the x values from within the third z quintile (i.e., the probability of missingness is highest for low values of z). To explore the impact of missingness in the long tail of the skewed distribution, we used a similar procedure to delete x for high values of z . Because there was no reason to believe that the pattern of missingness would matter in the symmetric distribution conditions, we reversed the missingness probabilities only in skewed design cells with an MAR mechanism. The MCAR and MAR deletion mechanisms produced a 20% missing data rate on x and xz . Although there is no way to speak to the generalizability of our deletion mechanism, the lack of previous research provides a rationale for studying an ideal situation where the cause of missingness is part of the analysis model. Further, a mechanism where missingness is a function of an observed predictor variable is optimal for complete-case analysis, a method that we use to benchmark the performance of maximum likelihood and multiple imputation. Finally, as noted previously, we chose not to manipulate the missing data rate because this factor tends to produce predictable results. Instead, we

Table 4
Population Parameters for the Simulation Studies

Parameter	Symmetric x and z		Skewed x and z	
	$R_{\Delta}^2 = .01$	$R_{\Delta}^2 = .05$	$R_{\Delta}^2 = .01$	$R_{\Delta}^2 = .05$
α	5.000	5.000	5.000	5.000
$\gamma_1 = \gamma_2$	5.000	5.000	5.000	5.000
γ_3	0.705	1.576	0.642	1.628
σ_{ϵ}^2	598.000	563.333	714.000	859.000

Note. The symmetric columns include the normal and kurtosis-only conditions.

chose a single missing data rate and a selection mechanism that we felt was extreme enough to expose potential problems.

Missing Data Handling

For each replication, we used Mplus to estimate the free mean and constrained mean interaction models (we did not include the default model because it is equivalent to the free mean model). Note that we used normal-theory (as opposed to robust) standard errors for all analyses because we believed that most substantive researchers would choose this option when implementing multiple imputation in SAS or SPSS. This ensured that the maximum likelihood and multiple imputation analyses invoked comparable assumptions.

We used the MI procedure in SAS to generate 20 imputed data sets for each replication. The imputation phase included the four analysis variables, all of which were in raw score format. After exploring the convergence behavior of data augmentation in a number of test data sets, we implemented a single data augmentation chain with 300 burn-in iterations and 300 between-imputation iterations (i.e., the first imputed data file was saved after 300 computational cycles and subsequent data sets were saved every 300 iterations thereafter). Prior to analyzing the filled-in data sets, we centered the lower order predictors at their means and rescaled the interaction using free mean and constrained mean centering (Equations 16 and 17, respectively). Finally, we used the REG to estimate the regression model and used the MIANALYZE procedure to combine the resulting estimates and their standard errors.

A large body of methodological literature has discounted complete-case analyses and other ad hoc missing data handling approaches (for a review, see Enders, 2010). Although deletion is generally a bad idea, complete-case analysis is known to produce valid estimates in regression models where missingness on a predictor depends on the observed values of another predictor (Little, 1992). Consequently, we included this approach in our simulations because it provides a useful benchmark for evaluating maximum likelihood and multiple imputation, and because it approach is still very common in published research articles.

Outcome Variables

For the zero effect size conditions, we examined the Type I error rates for the interaction coefficient. For the non-zero effect size conditions, we examined standardized bias, mean squared error, and confidence interval coverage. We computed standardized bias by dividing raw bias (the difference between an average estimate and the population parameter) by the standard deviation (i.e., empirical standard error) of the complete-data estimates within a particular design cell. This metric expresses bias in standard error units (Collins, Schafer, & Kam, 2001). We augmented standardized bias with the mean squared error (i.e., the average squared difference between an estimate and the population parameter). Because the mean squared error is the sum of sampling variance and squared bias, it quantifies the overall accuracy of an estimate.

Finally, we assessed confidence interval coverage by computing the proportion of replications where the 95% confidence interval contained the true population parameter. If parameter estimates and standard errors are accurate, confidence interval coverage for

a .05 alpha level should equal 95%. In contrast, if the standard errors are too small, confidence intervals will not capture the population parameter as frequently as they should, and coverage rates will drop below 95%. From a practical standpoint, coverage provides a benchmark for assessing the accuracy of the standard error estimates because it directly related to Type I error inflation (e.g., a 90% coverage value suggests a twofold increase in Type I errors, an 85% coverage value reflects a threefold increase, and so on).

Results

To begin, we examined the design cells where the population interaction equaled zero (i.e., the analysis model included an interaction effect when the population model did not). The primary concern was whether γ_3 exhibited excessive Type I errors. In the $N = 50$ condition, maximum likelihood estimation produced slightly elevated Type I error rates (e.g., values close to .07 were typical), but values were otherwise quite close to the nominal .05 rate. This was true for MCAR and MAR mechanisms. Turning to confidence interval coverage, all methods produced accurate coverage values for γ_1 and γ_2 . Complete-case analysis and multiple imputation produced somewhat lower coverage rates for the intercept coefficient, with most values ranging between .90 and .92. In the MAR simulation, complete-case analysis produced coverage values as low as .50 in the large sample condition. Maximum likelihood produced error rates close to the nominal level.

Parameter Recovery

Next, we examined parameter recovery in the design cells where the population interaction was non-zero. To examine the quality of the data generation, we examined raw and standard bias of the complete-data estimates. As expected, these estimates exhibited no systematic biases.

Estimates were uniformly accurate in the MCAR conditions; across all design cells and all missing data handling methods, the largest standardized bias value was approximately .06 (6% of a complete-data standard error unit), and the average standardized bias value was .002. This result is consistent with previous research and statistical theory (Rubin, 1976). Mean squared error (*MSE*) values from the MCAR simulations generally favored the MAR-based analyses, particularly when the interaction effect was small in magnitude. For the α and γ_2 coefficients (the regression intercept and the slope of the complete predictor, respectively), the complete-case *MSE* values were typically 15%–20% larger than those of the maximum likelihood and multiple imputation. Because *MSE* is inversely related to sample size, these differences indicate that a 15%–20% increase in the complete-case sample size is needed to achieve the same precision as an MAR-based approach. The complete-case *MSE* values for γ_1 (the incomplete predictor) were typically 5% larger, and *MSE* values for the interaction effect were virtually identical across methods. In the nonnormal conditions with a large interaction effect, *MSE* differences were less pronounced but still favored MAR-based estimation (e.g., the complete-case *MSE* values for the γ_2 coefficient was typically 5% larger than maximum likelihood and multiple imputation). Table 5 uses *MSE* ratios from the $N = 200$ condition to illustrate these trends. The *MSE* ratio is the fraction of the missing data *MSE* to the complete-data *MSE*, such that values closer to unity denote better

Table 5
Mean Squared Error (MSE) Ratios: MCAR Mechanism and $N = 200$

Distribution	Parameter	Small interaction effect					Large interaction effect				
		CCA	FMLV	CMLV	FMC	CMC	CCA	FMLV	CMLV	FMC	CMC
Normal	α	1.21	1.02	1.01	1.01	1.01	1.20	1.01	1.00	1.01	1.01
	γ_1	1.27	1.21	1.21	1.21	1.21	1.24	1.19	1.19	1.19	1.19
	γ_2	1.29	1.08	1.08	1.08	1.08	1.30	1.11	1.11	1.12	1.12
	γ_3	1.26	1.27	1.27	1.27	1.27	1.23	1.23	1.23	1.23	1.23
Skewed	α	1.27	1.02	1.02	1.02	1.02	1.26	1.03	1.04	1.03	1.04
	γ_1	1.32	1.29	1.29	1.30	1.30	1.29	1.29	1.29	1.28	1.28
	γ_2	1.29	1.13	1.13	1.14	1.14	1.33	1.22	1.22	1.22	1.22
	γ_3	1.34	1.35	1.35	1.36	1.36	1.29	1.32	1.32	1.31	1.31
Kurtotic	α	1.25	1.02	1.02	1.01	1.02	1.22	1.01	1.01	1.01	1.01
	γ_1	1.27	1.24	1.24	1.23	1.23	1.24	1.21	1.21	1.21	1.21
	γ_2	1.30	1.09	1.09	1.09	1.09	1.27	1.17	1.17	1.17	1.17
	γ_3	1.33	1.34	1.34	1.33	1.33	1.26	1.27	1.27	1.27	1.27

Note. Ratio of missing data *MSE* to complete-data *MSE*. The x and xz variables (γ_1 and γ_3 , respectively) have 20% missing data. MCAR = missing completely at random; CCA = complete-case analysis; FMLV = free mean latent variable model; CMLV = constrained mean latent variable model; FMC = free mean centering; CMC = constrained mean centering.

overall accuracy (e.g., a ratio of 1.20 indicates that the *MSE* for a missing data handling approach is 20% larger than that of the complete-data estimator). As seen in the table, the *MSE* ratios for the MAR-based approaches were virtually always lower than those of complete-case analysis, which owes to the fact that maximum likelihood and multiple imputation have less sampling variation.

Turning to the MAR mechanism, the combination of effect size and distribution shape had a complex influence on parameter recovery. Table 6 uses standardized bias values from the $N = 200$ condition to illustrate these results. Following Collins et al. (2001), we highlight bias values that exceed .40 (i.e., 40% of a

complete-data standard error unit) in absolute value. As seen in the table, complete-case analysis produced severely biased estimates of the intercept coefficient. In the large effect size conditions, the γ_1 coefficient (the slope of the incomplete predictor) also exhibited substantial biases. The MAR-based approaches also produced estimates with bias values exceeding .40, but the nature of this bias was somewhat idiosyncratic and dependent on distribution shape (e.g., symmetric distributions produced bias in the γ_2 coefficient, whereas the positively skewed distribution with missingness in the upper tail produced bias in γ_1).

Table 6
Standardized Bias: MAR Mechanism and $N = 200$

Distribution	Parameter	Small interaction effect					Large interaction effect				
		CCA	FMLV	CMLV	FMC	CMC	CCA	FMLV	CMLV	FMC	CMC
Normal	α	1.72	0.16	0.04	0.16	0.04	1.82	0.29	0.05	0.29	0.04
	γ_1	0.40	-0.06	-0.06	-0.08	-0.08	0.94	-0.12	-0.12	-0.14	-0.14
	γ_2	0.15	-0.20	-0.20	-0.19	-0.19	0.30	-0.44	-0.44	-0.43	-0.43
	γ_3	-0.05	-0.07	-0.07	-0.08	-0.08	0.02	-0.06	-0.06	-0.07	-0.07
Skewed (lower tail missing)	α	1.19	0.11	0.03	0.11	0.03	1.14	0.25	0.08	0.25	0.08
	γ_1	0.29	-0.02	-0.02	-0.05	-0.05	0.52	-0.10	-0.10	-0.12	-0.12
	γ_2	0.10	0.06	0.06	0.07	0.07	0.17	0.00	0.00	0.01	0.01
	γ_3	-0.03	-0.06	-0.06	-0.06	-0.06	-0.02	-0.11	-0.11	-0.12	-0.12
Skewed (upper tail missing)	α	-1.70	0.03	-0.07	0.04	-0.07	-1.54	0.05	-0.23	0.05	-0.23
	γ_1	-0.31	0.26	0.26	0.23	0.23	-0.81	0.42	0.42	0.38	0.38
	γ_2	-0.13	-0.02	-0.02	0.00	0.00	-0.26	0.21	0.21	0.22	0.22
	γ_3	0.01	0.07	0.07	0.06	0.06	-0.03	0.30	0.30	0.27	0.27
Kurtotic	α	1.66	0.18	0.03	0.18	0.03	1.69	0.36	0.10	0.36	0.10
	γ_1	0.39	-0.07	-0.07	-0.09	-0.09	0.87	-0.07	-0.07	-0.09	-0.09
	γ_2	0.10	-0.34	-0.34	-0.33	-0.33	0.25	-0.59	-0.59	-0.57	-0.57
	γ_3	0.01	-0.01	-0.01	-0.02	-0.02	-0.04	-0.10	-0.10	-0.11	-0.11

Note. Bold typeface denotes bias that exceeds .40 of a complete-data standard error unit. The x and xz variables (γ_1 and γ_3 , respectively) have 20% missing data. MAR = missing at random; CCA = complete-case analysis; FMLV = free mean latent variable model; CMLV = constrained mean latent variable model; FMC = free mean centering; CMC = constrained mean centering.

Table 7
 Mean Squared Error (MSE) Ratios: MAR Mechanism and $N = 200$

Distribution	Parameter	Small interaction effect					Large interaction effect				
		CCA	FMLV	CMLV	FMC	CMC	CCA	FMLV	CMLV	FMC	CMC
Normal	α	4.23	1.01	1.04	1.01	1.04	4.65	1.12	1.07	1.12	1.07
	γ_1	1.39	1.22	1.22	1.22	1.22	2.11	1.25	1.25	1.26	1.26
	γ_2	1.66	1.17	1.17	1.18	1.18	1.72	1.36	1.36	1.36	1.36
	γ_3	1.73	1.69	1.69	1.68	1.68	1.76	1.67	1.67	1.68	1.68
Skewed (lower tail missing)	α	2.74	1.02	1.01	1.02	1.01	2.63	1.08	1.02	1.08	1.02
	γ_1	1.23	1.19	1.19	1.20	1.20	1.41	1.18	1.18	1.18	1.18
	γ_2	1.18	1.05	1.05	1.06	1.06	1.21	1.05	1.05	1.05	1.05
	γ_3	1.21	1.18	1.18	1.18	1.18	1.21	1.16	1.16	1.15	1.15
Skewed (upper tail missing)	α	4.07	1.11	1.25	1.11	1.26	3.48	1.24	1.39	1.24	1.40
	γ_1	1.52	1.70	1.70	1.69	1.69	2.02	1.93	1.93	1.90	1.90
	γ_2	2.63	1.73	1.73	1.73	1.73	2.76	2.60	2.60	2.58	2.58
	γ_3	3.66	3.99	3.99	3.95	3.95	3.89	4.86	4.86	4.82	4.82
Kurtotic	α	4.00	1.03	1.05	1.03	1.05	4.15	1.19	1.09	1.19	1.09
	γ_1	1.43	1.34	1.34	1.34	1.34	2.01	1.28	1.28	1.29	1.29
	γ_2	1.63	1.31	1.31	1.31	1.31	1.68	1.65	1.65	1.64	1.64
	γ_3	1.89	1.85	1.85	1.85	1.85	1.92	1.86	1.86	1.86	1.86

Note. Ratio of missing data *MSE* to complete-data *MSE*. Bold typeface denotes cases where the complete-case *MSE* is lower than a missing at random (MAR)-based *MSE*. The x and xz variables (γ_1 and γ_3 , respectively) have 20% missing data. CCA = complete-case analysis; FMLV = free mean latent variable model; CMLV = constrained mean latent variable model; FMC = free mean centering; CMC = constrained mean centering.

Table 7 presents the corresponding *MSE* ratios from the $N = 200$ condition. Recall that *MSE* ratios reflect the fraction of the missing data *MSE* to the complete-data *MSE*, such that values closer to unity reflect greater overall accuracy. As seen in the table, the *MSE* ratios generally favored MAR-based estimation (i.e., *MSE* ratios were lower for these approaches), even for coefficients with larger bias values in Table 6 (e.g., the γ_2 estimate from the kurtotic condition). It is interesting that the complete-case estimates of γ_3 were somewhat more accurate in the positively skewed condition with missingness in the upper tail. Because this parameter exhibited minimal bias (see Table 6), the accuracy advantage is largely due to a smaller sampling variance. The same finding holds for γ_1 coefficient, but only in the small effect size condition. The table uses bold typeface to highlight *MSE* ratios that favor complete-case analysis.

Coverage

Finally, we examined confidence interval coverage. In the MCAR simulation, the vast majority of coverage values were quite close to the nominal 95% level. Coverage values for the regression slopes typically ranged between 93% and 95% and did not vary across conditions. Complete-case analysis and multiple imputation produced somewhat lower coverage values for the intercept coefficient (e.g., values close to 90% were typical), whereas maximum likelihood values for γ_0 were again close to the 95% level. We suspect that this discrepancy occurred because the maximum likelihood analyses treat the predictors as random variables with a distribution, whereas the ordinary least squares analyses treat predictors as fixed. The MAR coverage rates followed a similar pattern, except that the complete-case coverage values were quite low in some cases. Table 8 uses coverage values from the $N = 200$

condition to illustrate these results. For comparison purposes, we also include coverage values from the complete-data estimates.

Discussion

The existing missing data literature does not provide a clear prescription for estimating interaction effects with missing data, particularly when the interaction involves a pair of continuous variables. This article describes maximum likelihood and multiple imputation procedures for this common analysis problem. To this end, we outlined three latent variable model specifications for interaction analyses with missing data. These models apply procedures from the latent variable interaction literature—in particular, Marsh et al. (2004)—to analyses with a single indicator per construct (e.g., a regression analysis with scale scores). We also discussed multiple imputation for interaction effects, emphasizing an approach that applies standard imputation procedures (e.g., data augmentation; Schafer, 1997) to the product of two raw score predictors. A real data analysis and Monte Carlo simulations showed that maximum likelihood and multiple imputation produced remarkably similar estimates, even with relatively small samples. This result agrees with existing literature that demonstrates the equivalency of these two approaches (Collins et al., 2001; Schafer, 2003) and suggests that the choice of analytic method is largely one of personal preference (although maximum likelihood is arguably easier to implement for researchers who are facile with SEM software).

The methods that we outline in this article allow the researcher to freely estimate the product term mean (the free mean latent variable model and free mean centering) or partially constrain its value (the constrained mean latent variable model and constrained mean centering). Our results show that these two approaches

Table 8
Confidence Interval Coverage: MAR Mechanism and $N = 200$

Distribution	Parameter	Small interaction effect						Large interaction effect					
		COMP	CCA	FMLV	CMLV	FMC	CMC	COMP	CCA	FMLV	CMLV	FMC	CMC
Normal	α	0.904	0.539	0.938	0.953	0.892	0.897	0.913	0.521	0.940	0.967	0.887	0.908
	γ_1	0.945	0.930	0.952	0.952	0.953	0.953	0.945	0.855	0.940	0.940	0.938	0.938
	γ_2	0.943	0.945	0.948	0.948	0.949	0.949	0.951	0.940	0.943	0.943	0.939	0.939
	γ_3	0.949	0.943	0.941	0.941	0.944	0.944	0.960	0.959	0.950	0.950	0.958	0.958
Skewed (lower tail missing)	α	0.911	0.734	0.941	0.953	0.902	0.908	0.922	0.759	0.939	0.962	0.905	0.910
	γ_1	0.952	0.934	0.940	0.940	0.945	0.945	0.938	0.913	0.945	0.945	0.943	0.943
	γ_2	0.944	0.946	0.944	0.944	0.945	0.945	0.943	0.936	0.944	0.944	0.942	0.942
	γ_3	0.948	0.944	0.939	0.939	0.940	0.940	0.954	0.951	0.946	0.946	0.950	0.950
Skewed (upper tail missing)	α	0.911	0.575	0.912	0.923	0.950	0.960	0.922	0.646	0.920	0.943	0.949	0.967
	γ_1	0.952	0.939	0.942	0.942	0.935	0.935	0.938	0.890	0.919	0.919	0.919	0.919
	γ_2	0.944	0.952	0.914	0.914	0.912	0.912	0.943	0.942	0.850	0.850	0.846	0.846
	γ_3	0.948	0.943	0.940	0.940	0.938	0.938	0.954	0.948	0.941	0.941	0.941	0.941
Kurtotic	α	0.903	0.568	0.934	0.952	0.887	0.899	0.893	0.536	0.909	0.948	0.852	0.885
	γ_1	0.953	0.937	0.942	0.942	0.947	0.947	0.939	0.853	0.939	0.939	0.939	0.939
	γ_2	0.946	0.953	0.934	0.934	0.935	0.935	0.941	0.932	0.911	0.911	0.909	0.909
	γ_3	0.957	0.950	0.942	0.942	0.948	0.948	0.948	0.945	0.941	0.941	0.946	0.946

Note. Bold typeface denotes coverage values below 90%. With 2,000 replications, the standard error of the nominal .95 proportion is .005. The x and xz variables (γ_1 and γ_3 , respectively) have 20% missing data. MAR = missing at random; COMP = complete data analysis; CCA = complete-case analysis; FMLV = free mean latent variable model; CMLV = constrained mean latent variable model; FMC = free mean centering; CMC = constrained mean centering.

produce different estimates of the intercept coefficient when the mechanism is MAR. It is difficult to recommend one method over the other based on their mean squared errors. Considered as a whole, the constrained mean approaches produced smaller *MSE* values in a majority of design cells, but the exact pattern of results was a complex function sample size, distribution shape, and effect size. We tentatively recommend a constrained mean approach (latent variable model or post-imputation centering), acknowledging that there are situations where the free mean approaches will provide a lower *MSE* (e.g., positively skewed predictors with missingness in the upper tail). Note that the choice of centering method matters only when estimating effects that involve the intercept.

Because the methodological literature has largely discounted complete-case analyses, it may come as a surprise that maximum likelihood and multiple imputation generally provided only a modest improvement over deletion. It is important to note that complete-case analyses are known to produce valid estimates of regression slopes when (a) missingness on a predictor depends the observed values of another predictor, and (b) the incomplete predictor is linearly related to the observed predictor (Little, 1992). Our simulation design was optimal for complete-case analysis because both conditions were met. Based on the extant literature, we do not expect deletion to perform as well under different MAR configurations (e.g., missingness due to auxiliary variables not in the regression model).

Our study raises a number of avenues for future research. First, our simulation results underscore the need for additional analytic work. In models with linearly related variables, Yuan (2009) and Yuan and Bentler (2010) showed that normal-theory missing data handling methods yield consistent estimates under an MAR mechanism when normality is violated. However, the standardized bias

values from our simulations suggest that this property may not extend to non-linear models. Second, Yuan and Zhang (2012) recently outlined a two-stage missing data handling approach that first obtains robust M-estimates of the mean vector and the covariance matrix and subsequently uses the moments as input data for a structural equation model. Because the two-step approach down-weights outliers in the initial step, it may reduce bias when the mechanism is MAR. Finally, we did not investigate the performance of other common nonlinear effects (e.g., polynomials). For example, it is straightforward to extend the approaches in this article to quadratic effects because a quadratic term is simply the interaction between a variable and itself. Appendix H of the online supplemental materials describes the latent variable specification and post-imputation centering expression for quadratic regression models. Future simulation or analytic work could evaluate these approaches.

As with any Monte Carlo study, characteristics of our computer simulations may limit their generalizability. Although we attempted to choose conditions that would expose potential problems with the methods (e.g., a large proportion of missing data, relatively extreme distribution shapes, a strong selection mechanism), a number of limitations are worth considering. For example, we investigated an MAR mechanism where the propensity for missing data on one predictor was monotonically related to the values of the other predictor. Future studies could examine more complicated dropout mechanisms, perhaps with non-linear associations (e.g., “convex” or “sinister” processes; Collins et al., 2001). Non-ignorable (i.e., not missing not at random [NMAR]) mechanisms are another possibility that we did not consider. Future studies could also explore different distributional conditions. The lower order distributions exert a complex influence on the product term’s distribution (Aroian, 1947; Aroian, Taneja, & Cornwell,

1978; MacKinnon, 2008), and thoroughly manipulating these distributions could produce a number of interesting product term distributions. Our simulations suggest that the type of MAR mechanism and distribution shape (e.g., missingness in the upper vs. lower tail of a skewed distribution) may exert a complicated influence on parameter recovery. Future studies should attempt to clarify this issue.

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