Dynamic Structural Equation Modeling with Floor Effects

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Abstract

Intensive longitudinal data analysis, commonly used in psychological studies, often concerns outcomes that have strong floor effects, that is, a large percentage at its lowest value. Ignoring a strong floor effect, using regular analysis with modeling assumptions suitable for a continuous-normal outcome, is likely to give misleading results. This paper suggests that two-part modeling may provide a solution. It can avoid potential biasing effects due to ignoring the floor effect. It can also provide a more detailed description of the relationships between the outcome and covariates allowing different covariate effects for being at the floor or not and the value above the floor. A smoking cessation example is analyzed to demonstrate available analysis techniques.

Keywords: Intensive longitudinal data, two-part modeling, contemporaneous effects, smoking urge, negative affect

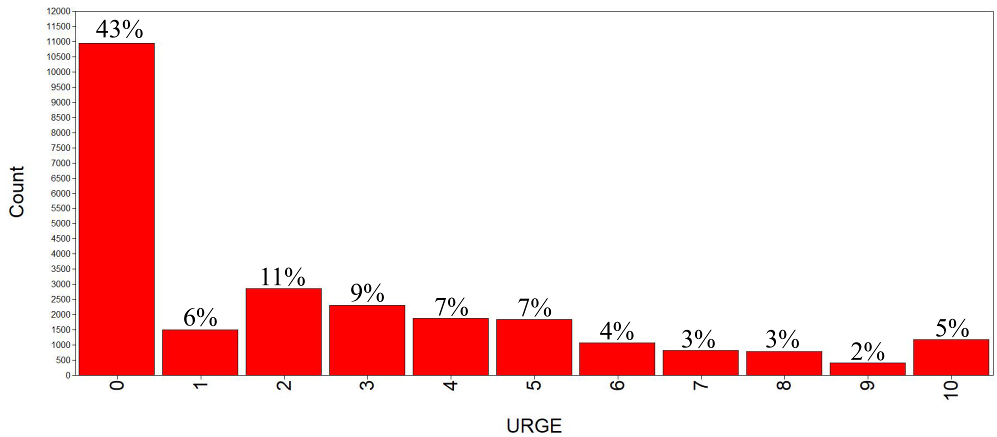
1 Introduction

Intensive longitudinal data analysis, also referred to as ecological momentary assessment analysis (Stone & Shiffman, 1994; Shiffman et al., 2008; Hamaker & Wichers, 2017), is now commonly used in psychological studies. Dynamic structural equation modeling (Asparouhov, Hamaker, Muthén, 2018) is a popular analysis technique for such data that has seen many applications (see, e.g., Hamaker et al., 2018; McNeish & Hamaker, 2020; McNeish et al., 2021; Santangelo et al., 2023; Savord et al., 2023; Hasl et al., 2023; Hamaker et al., 2023; Muthén et al., 2024). This technique allows both continuous and categorical outcomes. One type of outcome that is frequently observed in psychological studies, however, has not been covered so far. This is an outcome that is continuous but has a strong floor effect, that is, a large percentage at its lowest value. Such an outcome is for example seen in studies of mood, where negative affect may have floor effects accounting for substantial proportions of the observations. This paper is motivated by a smoking cessation study (further described below) where a key outcome is smoking urge after having quit smoking (Shiffman et al., 1997). Figure 1 shows the histogram for this outcome where the categories range from 0 (no urge) to 10 (extremely strong urge) with 43% of the observations at the lowest value of 0. Ignoring this strong floor effect, using regular analysis with modeling assumptions suitable for a continuous-normal outcome, is likely to give misleading results.

Two-part modeling provides a solution to the problem of analyzing data with strong floor effects. Two-part modeling was initiated in a regression context for the analysis of medical care expenditures (see, e.g., Duan et al., 1983) where there is an interest in predicting both whether any expenditures were incurred and predicting how high the expenditures were conditioned on that they were not zero. The two parts have different regression equations with possibly different predictors, allowing great modeling flexibility. Olsen and Schafer (2001) generalized this to the two-level case of repeated measurement modeling with an application to alcohol use among adolescents. Whereas in the regression situation, the two parts are uncorrelated and can be estimated separately, this is not the case in the two-level situation. The Olsen-Schafter two-part method uses maximum-likelihood estimation which requires numerical integration. It was implemented in Mplus (Muthén & Muthén, 1998-2017) and has been used in several psychological studies such as Brown et al. (2005), Vazsonyi and Keiley (2007), and Witkiewitz and Masyn (2008). In these studies with outcomes such alcohol, cigarettes, and drug use, there is an interest in both prevalence and frequency of use, that is, modeling both the probability of the floor value and modeling the values above the floor. This is where two-part modeling is natural. In this paper, two-part modeling is further extended to dynamic structural equation modeling of intensive longitudinal data as implemented in Mplus (Asparouhov et al, 2018). This implementation uses Bayesian estimation to accommodate more general models that would be intractable using maximum-likelihood estimation.

The section Two-Part Modeling provides the statistical background for two-part modeling and its extension to analysis of intensive longitudinal data. This is followed by the section Monte Carlo Simulations where two-part and regular analysis are contrasted. The section A Real-Data Example analyzes the smoking cessation data using three different types of two-part models for intensive longitudinal data. The Discussion section concludes.

Figure 1: Smoking urge histogram(43% at the floor value of zero)



2 Two-part modeling

Figure 2 describes the two-part model by the hypothetical case shown in the middle left distribution labelled "original". This outcome is split into two observed variables (squares in the figure), a binary 0/1 variable and a variable representing the positive part of the outcome. For observations where the binary variable equals zero, the positive variable has missing values. Olsen and Schafer (2001) recommends a transformation such as log to bring in the often long right tail of the distribution to make the positive part more closely approximate a normal distribution.[1] The right side of the figure shows these two new variables in a single-level wide 4-wave growth model with random intercept and random slope growth factors. The binary part uses a probit or logit model for the relation of the observed binary variables and the growth factors. The growth factors are regressed on a time-invariant covariate w. The two parts are correlated via w as well as via residual covariance between the growth factors. The parameters related to the growth factors are of primary interest. A strength of the two-part model is that the growth factors for the two parts can have different relations to w. For example, a treatment dummy variable can have an effect on one but not the other part. When the positive part has a limited number of scale categories, an ordinal version of the two-part model can be used as proposed in Muthén et al. (2016, 2023).

The two-part model may be expressed for individual i at timepoint t as

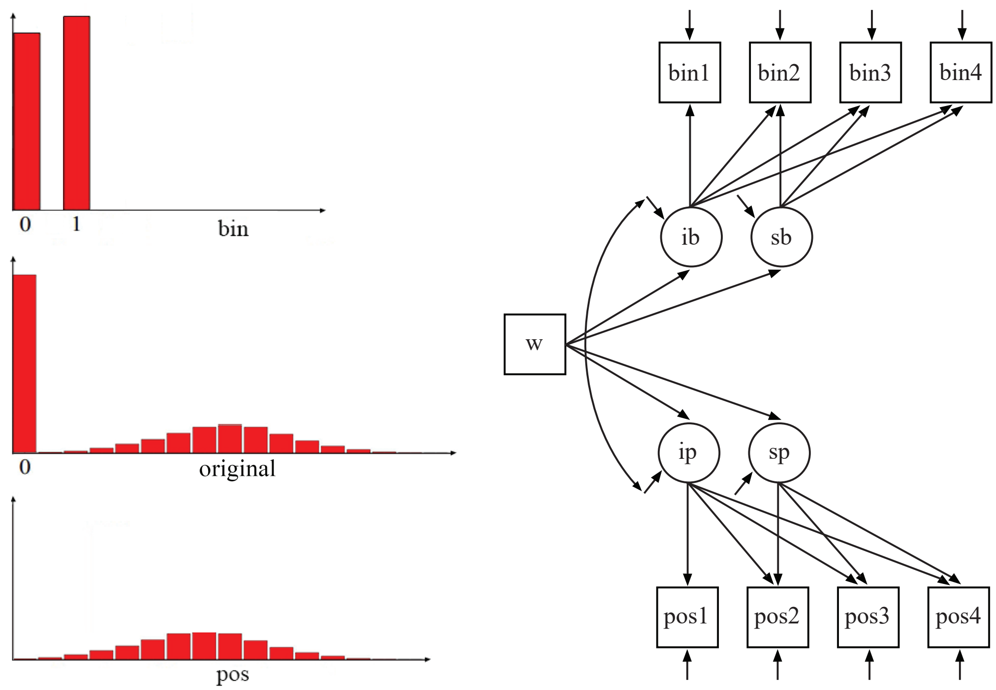
$$bin^*_{it} = \alpha_{1i} + \beta_1 w_i + \epsilon_{1it}, \tag{1}$$

$$pos = \alpha_{2i} + \beta_2 w_i + \epsilon_{2it}, \tag{2}$$

where $bin = 1$ when the latent response variable $bin^* > 0$ and is 0 otherwise. With a normally distributed ϵ_{1it} with $V(\epsilon_1) = 1$, (1) results in a probit regression of the binary part on the covariate w. The variable pos is observed when bin=1 and is missing otherwise. Here, α_{1i} and α_{2i} are random intercepts varying across individuals

[1] The creation of the binary and positive variables is automated in Mplus using the DATA TWOPART command.

Figure 2: Two-part growth model



with means α_1 and α_2 and variances ψ_1 and ψ_2. Noting that $E(y|w, bin = 0) = 0$, $E(y|w, bin = 1) = E(pos|w)$, the model implies the regression function

$$E(y|w) = P(bin = 0|w) \times 0 + P(bin = 1|w) \times E(pos|w), \tag{3}$$
$$= \Phi(\alpha_1^* + \beta_1^* w)\ (\alpha_2 + \beta_2 w), \tag{4}$$

where Φ is the normal distribution function and where α_1^* and β_1^* correspond to α_1 and β_1 divided by the bin^* standard deviation conditioned on w, $\sqrt{\psi_1 + 1/(1 - \rho^2)}$ where ρ is the AR(1) auto-correlation among the residuals. The larger ψ_1 and ρ are, the smaller the effect of w in the binary probability part $\Phi(\alpha_1^* + \beta_1^* w)$ of (4).

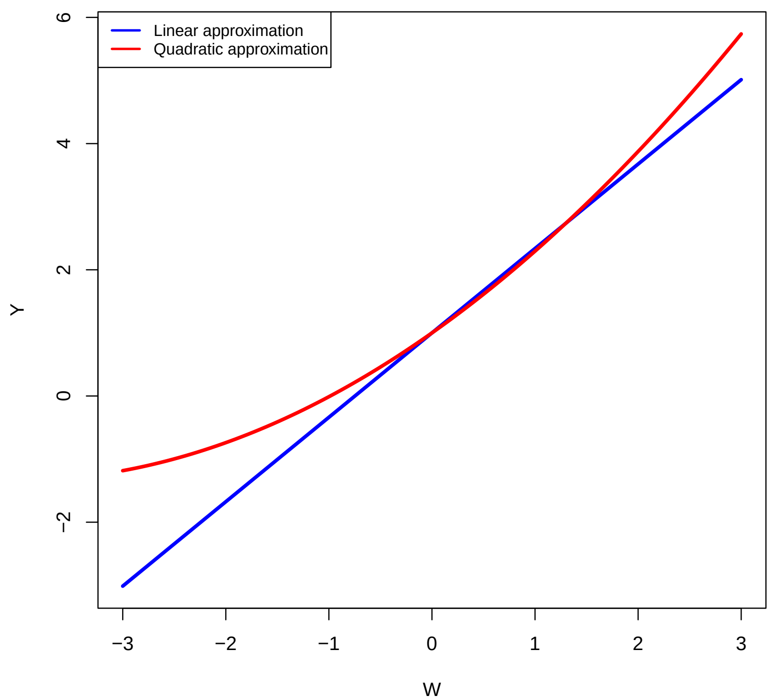
It is common to ignore the floor effect and use regular analysis with modeling assumptions suitable for a continuous-normal outcome including a linear relationship for the outcome regressed on covariates. The two-part model of (1) and (2) does not, however, imply a linear model but a non-linear model. Using a quadratic Taylor expansion of (4), it can be shown that the non-linear relationship can be approximated as

$$E(y|w) \approx (\frac{1}{\sqrt{2\pi}}(\alpha_1^* + \beta_1^* w) + 1/2)(\alpha_2 + \beta_2 w), \tag{5}$$

A linear approximation can be expressed as

$$E(y|w) \approx (\frac{1}{\sqrt{2\pi}}(\alpha_2 \beta_1^* + \alpha_1^* \beta_2) + \beta_2/2)\ w. \tag{6}$$

Figure 3: Regressions based on a two-part model



The linear approximation corresponds to the linear regression used when ignoring the floor effect. Equation (6) shows that the linear regression slope is a complex combination of products of intercepts and slopes for the binary and positive parts. Figure 3 shows the quadratic and linear approximations for an example with R^2 0.5 for both (1) and (2).

2.1 Two-part dynamic structural equation modeling

The extension of the two-part method to intensive longitudinal data considered in this paper uses dynamic structural equation modeling (DSEM; Asparouhov et al., 2018). DSEM is based on two-level analysis (repeated measurements within individuals) and Bayesian estimation. The two-part DSEM model is shown in Figure 4 for the case of a random intercept. Unlike Figure 2, there is no random slope (no trend) but this can be added as well as illustrated in the Real-Data Example section. The model is drawn for outcomes at two adjacent time points t and $t-1$ representing the whole time series. Each observed variable is decomposed into latent within- and between-level variables (cf. Equations (1), (2)). As an example, the continuous variable pos is expressed as

$$Level\ 1: \ pos_{it} = pos_{Bi} + \rho(pos_{it-1} - pos_{Bi}) + \epsilon_{it}, \tag{7}$$

$$Level\ 2: \ pos_{Bi} = \alpha + \beta\ w_i + \delta_i. \tag{8}$$

Here, ρ is the auto-regressive coefficient of lag 1 seen in Figure 4. Note that this two-level model has a random intercept pos_{Bi} which is also used to center the pos_{it-1} predictor. The latent variable centering is essential to avoiding biases (Nickell, 1981; Asparouhov & Muthén, 2019). Equation (7) can be expressed as:

$$\underbrace{pos_{it} - pos_{Bi}}_{y_{Wit}} = \rho(\underbrace{pos_{it-1} - pos_{Bi}}_{pos_{Wit-1}}) + \epsilon_{it}, \tag{9}$$

emphasizing that there is a within- and between-level model part in line with Figure 4,

$$Within: \ pos_{Wit} = \rho\ pos_{Wit-1} + \epsilon_{it}, \tag{10}$$

$$Between: \ pos_{Bi} = \alpha + \beta\ w_i + \delta_i. \tag{11}$$

The specification of the within and between parts of the model translates into the specification in the Mplus software (Muthén & Muthén, 1998-2017).

Because of the binary part of the model, two-part DSEM benefits from the Asparouhov et al. (2018, pp. 362-363) development for categorical outcomes where the decomposition is made for continuous latent response variables underlying the observed variables. This latent response variable is the same as bin^*_{it} in (1). The modeling of this variable is analogous to that of the *pos* variable in (7) - (11).

In the within part of Figure 4, the variables correspond to the Figure 2 residuals (short arrows) at the different timepoints. In Figure 2, they are not correlated over time for either the binary or the positive parts but they could be. Figure 4 includes these correlations which is natural with intensive longitudinal measurements which are spaced closely in time. Within-level cross-lagged effects between the two variables are identified but can be excluded for simplicity since they have little effect on the between-level part of the model which is the focus of the analysis. Within-level residual

Figure 4: Two-level two-part dynamic structural equation model (DSEM)

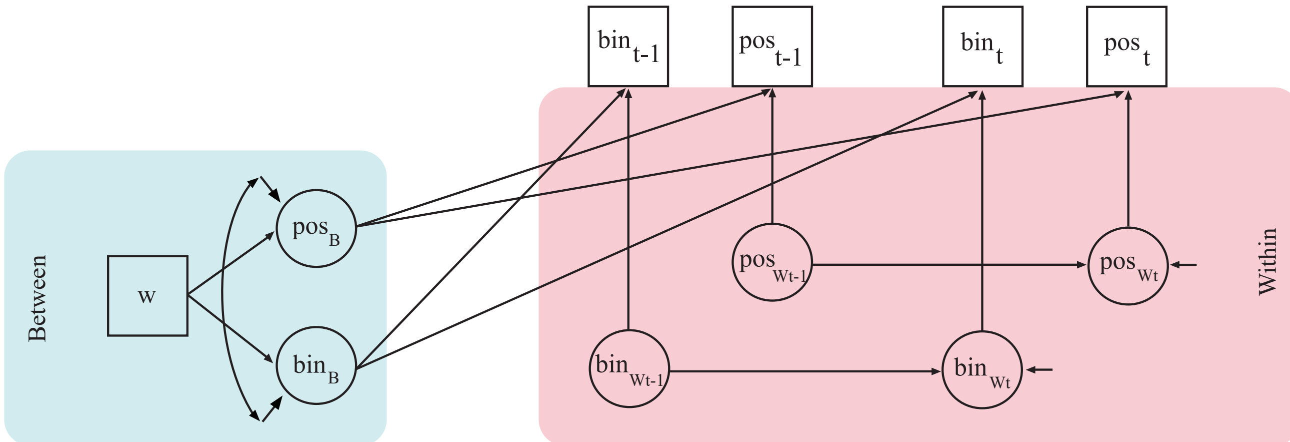
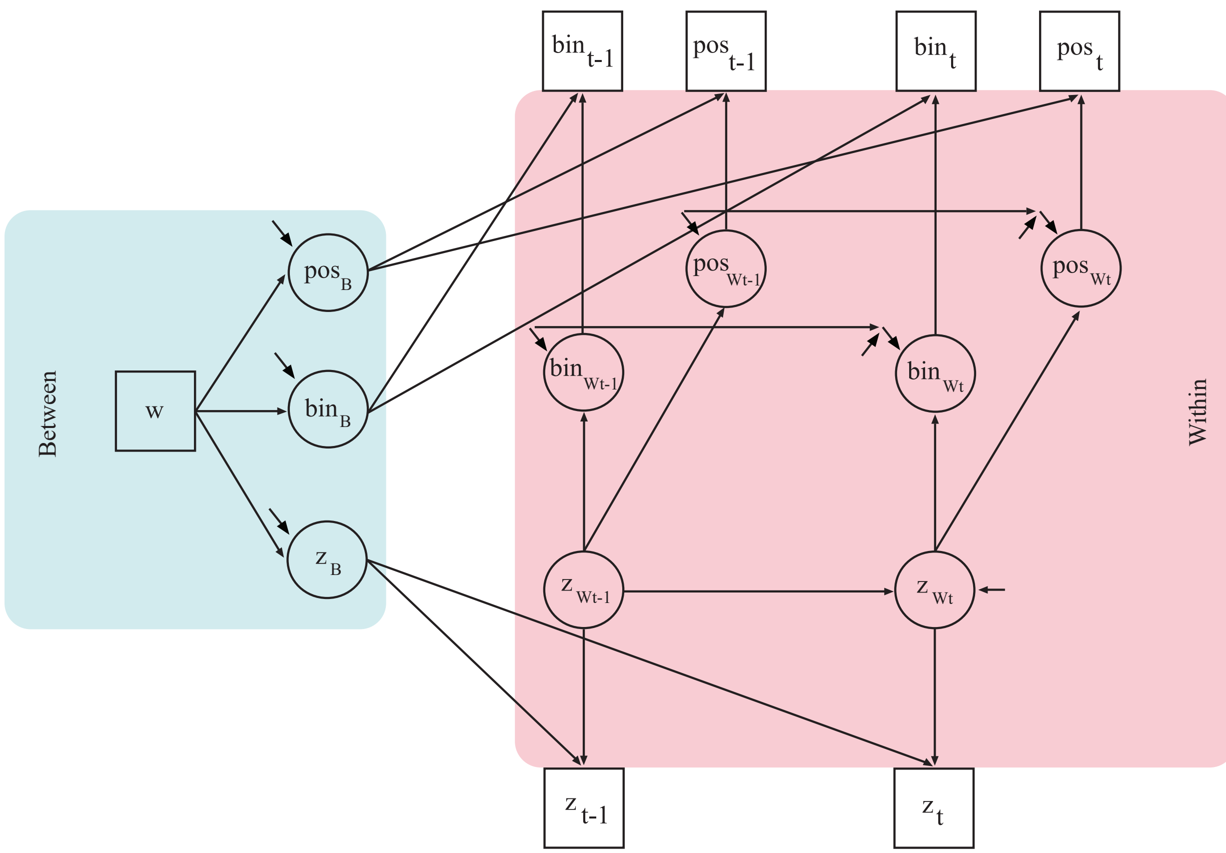


Figure 5: Bivariate two-level two-part RDSEM



correlation is also excluded since it has little empirical support due to the positive part not being observed when the binary observed variable is zero.

Figure 5 shows a bivariate two-level two-part DSEM model where the added outcome z influences the binary and positive parts of the first outcome but does not need a two-part treatment itself. This is referred to as RDSEM because the within-level auto-regressions are for the residuals of the contemporaneous regressions on z, not for the full within part of the variables.

While two-level DSEM and RDSEM decompose the observed variable into two latent variables,

$$y_{it} = \underbrace{y_{Bi}}_{\text{Between person}} + \underbrace{y_{Wit},}_{\text{Within person}} \tag{12}$$

cross-classified DSEM and RDSEM decompose the observed variable into three latent variables,

$$y_{it} = \underbrace{y_{Bi}}_{\text{Between person}} + \underbrace{y_{Wit}}_{\text{Within person}} + \underbrace{y_{Tt}.}_{\text{Between time}} \tag{13}$$

Here, y_{Bi} refers to variation between persons that is constant over time, while y_{Tt} refers to variation between timepoints that is constant over persons. The latent variables y_{Bi}, y_{Wit}, y_{Tt} are specified as normally distributed where y_{Wit} and y_{Tt} have zero means.

Figure 6 shows an example of the three parts of the model, Between ID (person), Within, and Between Time. The within part of the model has a contemporaneous regression of y on z and lag 1 auto regressions among the residuals while the between time part contributes time-specific influence.

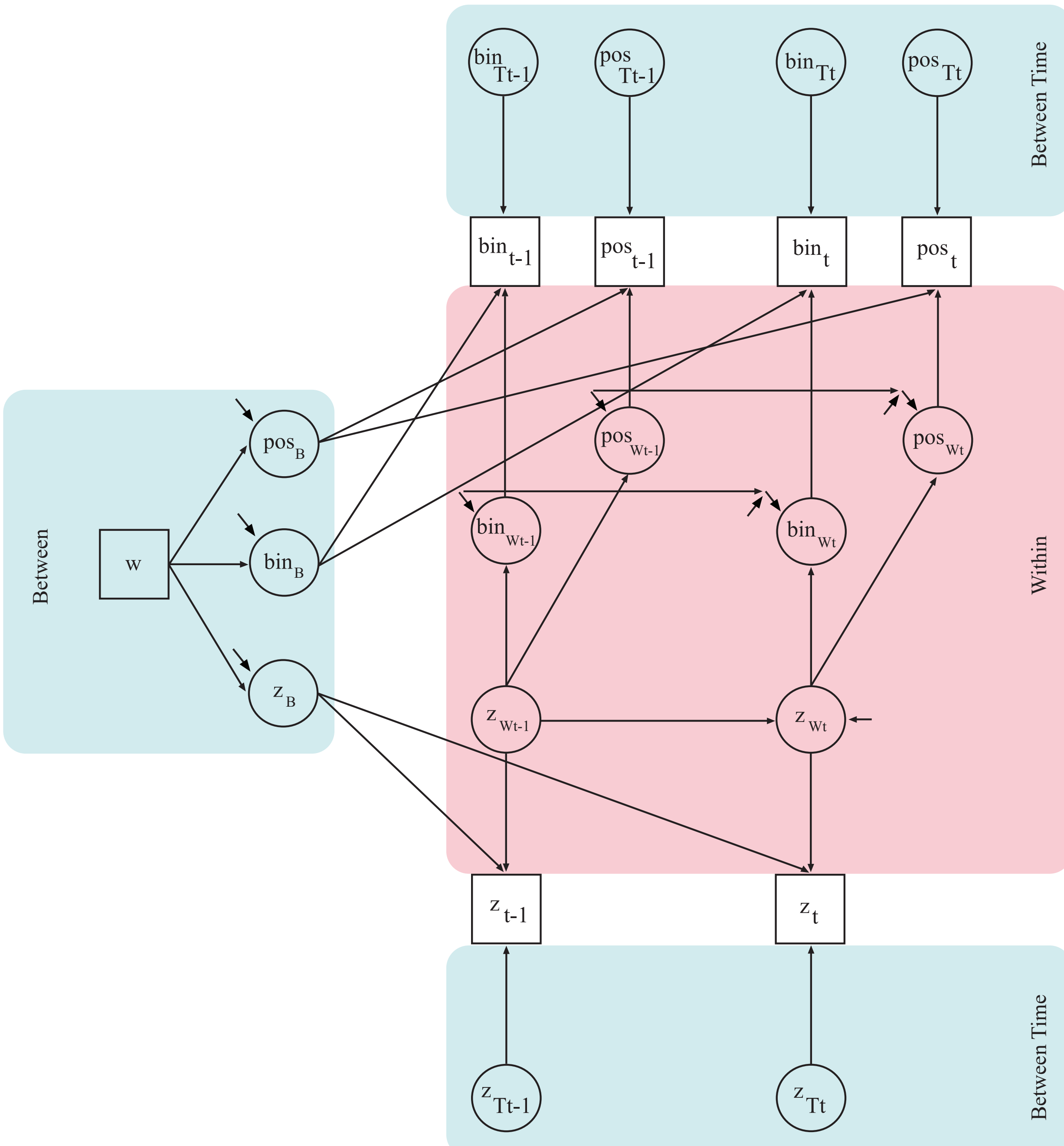
The advantage of cross-classified DSEM is that the y_T term can discover trends over time. The model is an essential tool of cycles analysis (Muthén et al, 2024). The model can be estimated without imposing a specific trend function. The T y_{Tt} estimates can be plotted against time to generate ideas for trend modeling. The trend modeling can then be carried out in either cross-classified or twolevel DSEM/RDSEM.

3 Monte Carlo simulations

The aims of the Monte Carlo simulations are to study the bivariate two-level two-part RDSEM model of Figure 5 in terms of how well parameter values can be recovered, the quality of standard error estimation, the coverage, and the power to detect effects. Parameter values are based on a simplified version of the two-part analyses of the smoking urge data studied in the examples section. A common setting with sample size of N = 200 and 50 timepoints is chosen. Data are generated for an outcome with a 50% floor effect. It should be noted that for the positive variable in the two-part modeling, the effective cluster size is only 25 given that the variable has missing values in 50% of the defined time blocks. The within-level predictor z and the between-level predictor w are normally distributed.

Table 1 shows the results where the top and bottom parts of the table differ only in the magnitude of the between-level regression coefficients of the W covariate for the binary and positive parts. Standardized values of 0.05 versus 0.2 are used to reflect a negligible effect versus a substantial effect. The first column of the table refers to the parameters. The Z variable is the predictor of the two-part outcomes and exists on both the within and between levels using a latent variable decomposition (Asparouhov

Figure 6: Bivariate cross-classified two-part RDSEM



et al., 2018). BINˆ ON BINˆ1 refers to the lag 1 auto-correlation for the binary part and corresponds to the regression between the latent variables at time t and $t-1$ in the within part of Figure 5. The analogous notation is used for POS and Z. The values used for the data generation are given in the column labeled Population. The next two columns give the parameter estimate average and standard deviation. It is seen that the averages agree well with the population values. The column S.E. Average shows that the average standard errors agree reasonably well with the standard deviations of the estimates. M.S.E. stands for mean squared error and will not be considered here. The 95% Cover column shows values close to the expected 95% coverage for all estimates. The %Sig column gives estimates of the power to reject the hypothesis that the parameter estimate is zero. The power is high for all within-level parameters but is low for the between-level parameters of size 0.05 as expected. A much larger N would be needed to get the power for those parameters close to 0.80.

Table 2 shows results from a regular bivariate two-level RDSEM Monte Carlo simulation where the floor effect is ignored. The data were generated by the same two-part model as in Table 1 but analyzed without two-part modeling. The column of population values is not included because different parameters are estimated. For example, the coefficient for the regression of Y on W on the between level refers to the best linear regression fitted to the non-linear relationship between Y and W. An approximate value for this linear regression coefficient can be obtained from (6). These values are 0.17 and 0.31 for the top and bottom parts, respectively. The table shows that the average estimates are very close to those two values. The average estimate of 0.2990 in the bottom part of the table illustrates the fact that the estimate may be larger than that of either the binary or positive parts of the two-part model. The focus of Table 2, however, is on the power for the between-level regressions addressing the question of whether the effect of W on Y is likely to be detected. In the top part of the table, the power is estimated as only 0.25 and in the bottom part the 0.58 value is also falling far below the desired power of at least 0.80. The corresponding two-part values in Table 1 are considerably higher, 0.81 and 0.75. This implies that if data are generated by a two-part model and the floor effect is ignored, it is quite possible that W is overlooked as an important predictor on the between level. The example section shows similar results. The difference between the 0.25 and 0.58 power estimates in the top and bottom parts of the table is due to the difference in estimates with averages 0.1705 versus 0.2990. The standard errors are approximately the same. In this simulation, the larger average and larger power occur when the binary part has the larger effect. The standard errors are almost twice as large as those of the binary and positive parts in the two-part modeling of Table 1. Larger standard errors are to be expected given that the model is incorrect. The corresponding loss of power is not seen on the within level due to the extra information derived from the repeated measurements. The standard error for Y ON Z is, however, inflated as compared to the standard errors for U ON Z and POS ON Z in Table 1 which means that with smaller regression coefficients there may be important power loss.

4 A real-data example

The two-part modeling will be illustrated using data from a smoking cessation study (Shiffman et al., 1997). The sample consists of smokers who had decided to try to quit.

Table 1: Monte Carlo simulation study of two-level RDSEM using two-part analysis.

	ESTIMATES			S.E.	M.S.E.	95%	% Sig
	Population	Average	Std. Dev.	Average		Cover	Coeff
Population between-level values: Bin ON W = 0.05, Pos ON W = 0.2							
Within Level							
BIN ON							
Z	0.050	0.0500	0.0144	0.0148	0.0002	0.940	0.960
POS ON							
Z	0.200	0.1965	0.0154	0.0144	0.0002	0.930	1.000
BIN^ ON							
BIN^1	0.300	0.3001	0.0196	0.0185	0.0004	0.940	1.000
POS^ ON							
POS^1	0.300	0.3006	0.0169	0.0160	0.0003	0.940	1.000
Z^ ON							
Z^1	0.300	0.2990	0.0103	0.0100	0.0001	0.910	1.000
Between Level							
BIN ON							
W	0.050	0.0504	0.0672	0.0739	0.0045	0.960	0.080
POS ON							
W	0.200	0.2001	0.0744	0.0752	0.0055	0.960	0.810
Z ON							
W	0.200	0.2105	0.0752	0.0724	0.0057	0.950	0.850
Population between-level values: Bin ON W = 0.2, Pos ON W = 0.05							
Within Level							
BIN ON							
Z	0.050	0.0503	0.0147	0.0148	0.0002	0.950	0.930
POS ON							
Z	0.200	0.1966	0.0156	0.0144	0.0003	0.890	1.000
BIN^ ON							
BIN^1	0.300	0.3002	0.0193	0.0187	0.0004	0.920	1.000
POS^ ON							
POS^1	0.300	0.3010	0.0166	0.0161	0.0003	0.920	1.000
Z^ ON							
Z^1	0.300	0.2988	0.0103	0.0100	0.0001	0.910	1.000
Between Level							
BIN ON							
W	0.200	0.2000	0.0695	0.0742	0.0048	0.960	0.750
POS ON							
W	0.050	0.0520	0.0748	0.0753	0.0055	0.980	0.120
Z ON							
W	0.200	0.2105	0.0750	0.0730	0.0057	0.950	0.820

Table 2: Monte Carlo simulation study of two-level RDSEM using regular analysis.

	ESTIMATES Average	ESTIMATES Std. Dev.	S.E. Average	% Sig Coeff
Population between-level values: Bin ON W = 0.05, Pos ON W = 0.2				
Within Level				
Y ON				
Z	0.1662	0.0234	0.0215	1.000
Y^ ON				
Y^1	0.1795	0.0127	0.0100	1.000
Z^ ON				
Z^1	0.2992	0.0102	0.0098	1.000
Between Level				
Y ON				
W	0.1705	0.1252	0.1346	0.250
Z ON				
W	0.2147	0.0747	0.0740	0.840
Population between-level values: Bin ON W = 0.2, Pos ON W = 0.05				
Within Level				
Y ON				
Z	0.1662	0.0226	0.0214	1.000
Y^ ON				
Y^1	0.1795	0.0127	0.0100	1.000
Z^ ON				
Z^1	0.2992	0.0102	0.0098	1.000
Between Level				
Y ON				
W	0.2990	0.1242	0.1338	0.580
Z ON				
W	0.2147	0.0747	0.0740	0.840

Ecological momentary assessments (EMA) were made several times a day for a month. Random prompts were issued by a handheld device on average five times a day for reporting on smoking urge as well as negative affect. In addition to the random prompts, several more event-oriented self reports were also made during temptations to smoke and brief smoking lapses (specific episodes of smoking). Such lapses were typically limited to a few puffs, and were considered related to but distinct from the occurrence of relapse, which represented a more substantial resumption of regular smoking (smoking 5 or more cigarettes per day for 3 consecutive days). Figure 1 shows the histogram for the smoking urge outcome where the categories range from 0 (no urge) to 10 (extremely strong urge) with 43% of the individuals at the lowest value of 0. The negative affect variable does not have a floor effect but is approximately normally distributed. The lack of a floor effect for this variable is understandable because this variable, a factor score summarizing 11 underlying items that also included positive emotions, is bi-polar, such that negative values represent very positive affect rather than merely the absence of negative affect. The analyses comprise 235 individuals of whom 152 or 65% lapsed and 45 or 19% progressed to relapse during the study period (others could have relapsed later).

To synchronize the random times of observations between the individuals of the sample, the Asparouhov et al. (2018) DSEM analysis discretizes the exact time of the reports into 2-hour bins, inserting missing data rows for timepoints not observed for the individual.[2] Other bin sizes ranging from 1 hour to 4 hours give similar results. 2-hour bins are chosen to balance the need to minimize the discrepancy between observed and discretized time and to obtain sufficient data coverage given the missing data especially for the positive variable of the two-part model.[3]

The two-part modeling in this example does not apply the log transformation suggested in Olsen and Schafer (2001) for the positive part.[4] This is not necessary in this example because the skewness of the positive part is not very large. The results are quite similar with and without the transformation. Mplus inputs for the analyses are shown in the appendix.

4.1 Bivariate two-level two-part RDSEM of smoking urge related to negative affect

The first analysis uses the bivariate two-level two-part RDSEM model of Figure 5. The binary and positive variables of the figure refer to the smoking urge variable while z is represented by negative affect. Time-varying dummy variables for temptation and lapses reporting are added on the within level (zero values on both dummies correspond to reports from random prompts). The between-level covariate w is represented by gender, age, and average number of cigarettes smoked per day before quitting.

Table 3 shows the two-part analysis results using standardized estimates.[5] The right-most column uses asterisks to denote when the 95% credibility interval (CI) does not include zero, that is, the estimate is significant using frequentist terms. On the

[2]This uses the TINTERVAL option in Mplus which is discussed in Hamaker et al., 2023 and in Mplus Web Talk No. 6.

[3]The coverage for the positive variable is 0.243.

[4]This uses the Mplus option TRANSFORM=NONE.

[5]Binary covariates are not standardized.

within level, both the binary and positive parts are significantly influenced by negative affect with a larger point estimate for the positive part, that is, the extent of the smoking urge (not just its presence). As compared to reporting at random prompts, the temptation and lapse reporting is connected with higher smoking urge as expected. The autoregression is estimated at a high value of 0.746 for the binary part. As will be seen in the analysis of the next section, however, this may be an artefact of a strong trend.

The between-level results are of primary interest. It is seen that the binary and positive parts have different significant predictors, average number of cigarettes versus age. How heavy a smoker a person was before trying to quit as measured by the number of cigarettes smoked is an expected predictor, but it is significant only for having an urge to smoke or not (BIN), not for the extent of the smoking urge (POS). Given that age may correlate with how long a person has been a smoker, it is also expected that age is a significant predictor of smoking urge, but this is the case only for the extent of smoking urge, not whether there is an urge or not – the opposite of the pattern for heaviness of smoking.

Table 4 shows the results using regular analysis ignoring the floor effect. Here, the between-level results show that only the average number of cigarettes is a significant predictor of smoking urge, not age.[6] In conclusion, as compared to regular analysis, the two-part analysis gives a more nuanced picture of smoking urge in term of predictors for whether or not there is an urge versus the extent of the urge. In this example, however, there is not a drastic difference in the general conclusion about important predictors. The large difference in standard errors between regular and two-part analysis seen in the Monte Carlo simulation section does not materialize here. This may be due to several differences between the simulations and the smoking urge data. For example, the coverage in the simulation study is about twice as large as in this example. The lower coverage in the example is largely a consequence of the random timepoints of the measurements, leading to insertion of missing data rows for many 2-hour bins. In contrast, the simulations have no such missing data and are more representative of designs with fixed timepoints such as daily diary studies. Also, the simulations use 50 timepoints whereas this example has 320 timepoints. Furthermore, the auto-correlation is much higher in the example than in the simulations. As will be shown in the next set of analyses, the inflated auto-correlation is due to ignoring trends in smoking urge.

4.2 Bivariate cross-classified two-part RDSEM analysis of trends

Figure 6 showed an example of a bivariate cross-classified two-part RDSEM model. This model will be used here for smoking urge related to negative affect in an effort to study trends in these variables over time after quitting. It is assumed that the degree of smoking urge declines over time, as this has been observed (see also Shiffman et al., 1997). This trend can be captured by the estimated scores for the Between Time part of the model.

Figure 7 shows the $T\ y_{Tt}$ estimates for the binary and positive parts plotted against

[6] The age effect is, however, similar to that of the two-part results for the extent of smoking urge (POS), both in terms of point estimate and credibility interval with the lower limit of the interval being barely above zero for two-part and barely below zero for regular analysis.

Table 3: Two-part RDSEM of smoking urge related to negative affect: Standardized estimates

	Estimate	Posterior S.D.	95% C.I. Lower 2.5%	Upper 2.5%	Significance
Within Level					
BIN ON					
NEGAFF	0.149	0.010	0.129	0.168	*
TEMPTATION	0.487	0.031	0.426	0.550	*
LAPSE	1.075	0.049	0.994	1.180	*
POS ON					
NEGAFF	0.239	0.008	0.223	0.255	*
TEMPTATION	-0.084	0.021	-0.126	-0.044	*
LAPSE	0.422	0.027	0.368	0.474	*
BIN^ ON					
BIN^1	0.746	0.009	0.725	0.762	*
POS^ ON					
POS^1	0.372	0.010	0.351	0.392	*
NEGAFF^ ON					
NEGAFF^1	0.531	0.006	0.519	0.542	*
Between Level					
BIN ON					
MALE	0.007	0.127	-0.243	0.256	
AGE	0.077	0.063	-0.045	0.199	
AVECIGS	0.178	0.066	0.049	0.303	*
POS ON					
MALE	-0.340	0.142	-0.614	-0.057	*
AGE	0.129	0.064	0.003	0.255	*
AVECIGS	0.086	0.067	-0.044	0.218	
NEGAFF ON					
MALE	-0.010	0.137	-0.280	0.254	
AGE	0.075	0.065	-0.051	0.204	
AVECIGS	0.149	0.067	0.006	0.275	*

Table 4: Regular RDSEM of smoking urge related to negative affect: Standardized estimates

	Estimate	Posterior S.D.	95% C.I. Lower 2.5%	Upper 2.5%	Significance
Within Level					
URGE ON					
NEGAFF	0.205	0.006	0.193	0.217	*
TEMPTATION	0.238	0.017	0.205	0.270	*
LAPSE	0.814	0.023	0.768	0.857	*
URGEˆ ON					
URGEˆ1	0.314	0.007	0.300	0.328	*
NEGAFFˆ ON					
NEGAFFˆ1	0.531	0.006	0.520	0.543	*
Between Level					
URGE ON					
MALE	-0.214	0.126	-0.457	0.038	
AGE	0.116	0.060	-0.003	0.232	
AVECIGS	0.192	0.064	0.061	0.318	*
NEGAFF ON					
MALE	-0.025	0.134	-0.284	0.246	
AGE	0.077	0.064	-0.049	0.198	
AVECIGS	0.144	0.067	0.013	0.265	*

the timepoints of the approximate month of the study. A strong negative trend is observed for both parts. This trend was not accounted for in the previous two-level two-part analysis. The plot indicates that the trend flattens out after about two weeks (midway of the x-axis). Figure 8 magnifies the plot for the first week of the binary part. Apart from the negative trend, there is also evidence of a cyclic feature with a higher tendency to report some smoking urge during the middle of the day. The cyclicity appears to disappear after the first two weeks. This cyclicity could be modeled in line with Muthén et al. (2024) but will not be pursued here. Negative affect shows a small negative trend.

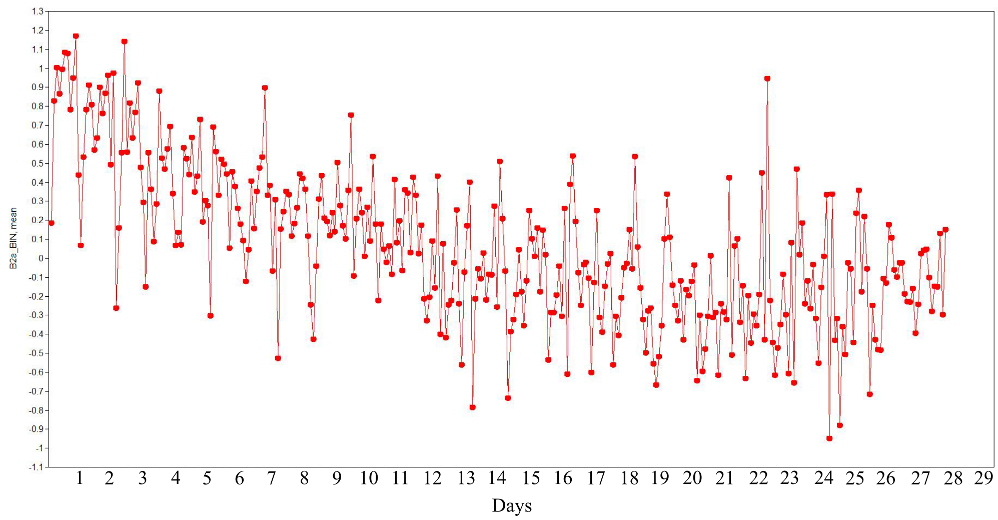
4.3 Two-level two-part RDSEM analysis taking time trend and relapse into account

The time trends revealed in the above cross-classified analysis can be modeled in either a cross-classified or two-level analysis. A two-level analysis is chosen here. This uses the type of model shown in Figure 5 where a time variable is added to the within part of the model influencing bin, pos, and z (negative affect). In line with Figure 7, a linear trend is applied for the first two weeks with no trend after that. As a second model feature, a binary distal outcome is added, namely a relapse indicator for whether or not the person resumed regular smoking. On the between level, this is captured by the mediation model shown in Figure 9 which specifies that the random effects act as mediators between the covariates and the relapse outcome. Here, bin and pos refer to the random intercepts, sb and sp refer to the random trends (random slopes for the linear decline) for the binary and positive parts, respectively, and na refers to the random intercept of negative affect. Direct effects from the covariates to the relapse outcome are also included in the analysis but not drawn in the figure.

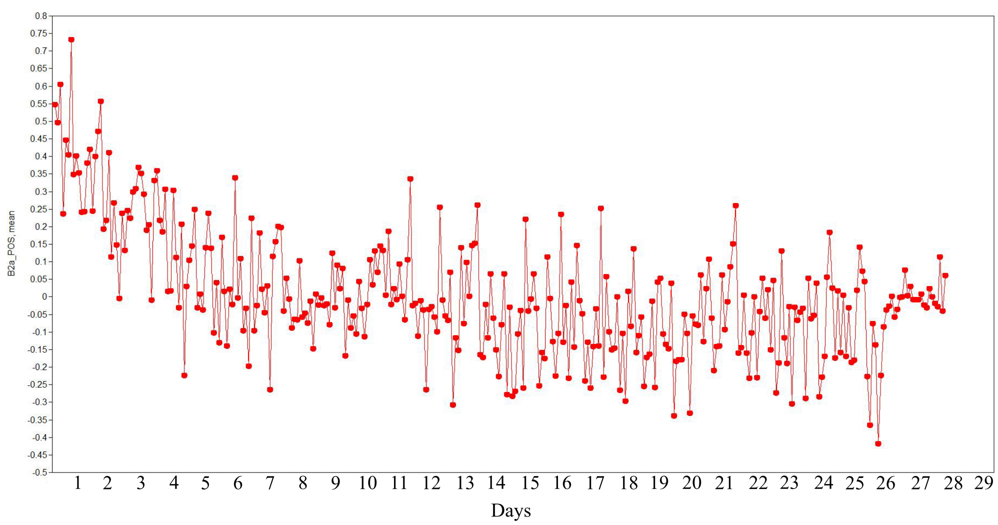
Table 5 shows the standardized between-level results for two-level two-part RD-SEM mediation model of smoking urge related to negative affect, time, and relapse. The binary part is significantly influenced by age and average number of cigarettes whereas the positive part is significantly influenced by gender. Specifically, older and heavier smokers are more likely to experience some craving, whereas when participants do report craving, males report lower intensity of craving, but age and heaviness of smoking do not influence craving intensity. The random slopes for the trends of the binary and positive parts are not significantly influenced by any of the covariates. The relapse outcome is significantly influenced by the random intercept for the positive part. As expected, the higher the intercept, the more likely smokers with more intense cravings are to relapse. The relapse outcome is also influence by age with older individuals having a lower relapse probability. The random slopes of the trend have no significant influence on the relapse outcome. With the POS random intercept as the only mediator with a significant effect on relapse, indirect effects on relapse appear for the influence of gender with males having a lower POS random intercept which in turn lowers the relapse probability. The lower relapse probability is due to the product of the negative male coefficient and the positive relapse coefficient resulting in a negative indirect effect.[7] The direct effect of age indicates that older persons are less likely to

[7]Regular indirect effects computed as products of coefficients are correct for the underlying continuous latent response variable behind the binary relapse outcome. Calculation of indirect effects for the probability of a binary outcome using causal inference based on counterfactuals is described in Muthén and Asparouhov

Figure 7: Estimated between time scores for the binary and positive parts of the cross-classified two-part RDSEM analysis



(a) Binary part



(b) Positive part

Figure 8: Estimated between time scores for the first 7 days of the binary part of the cross-classified two-part RDSEM analysis

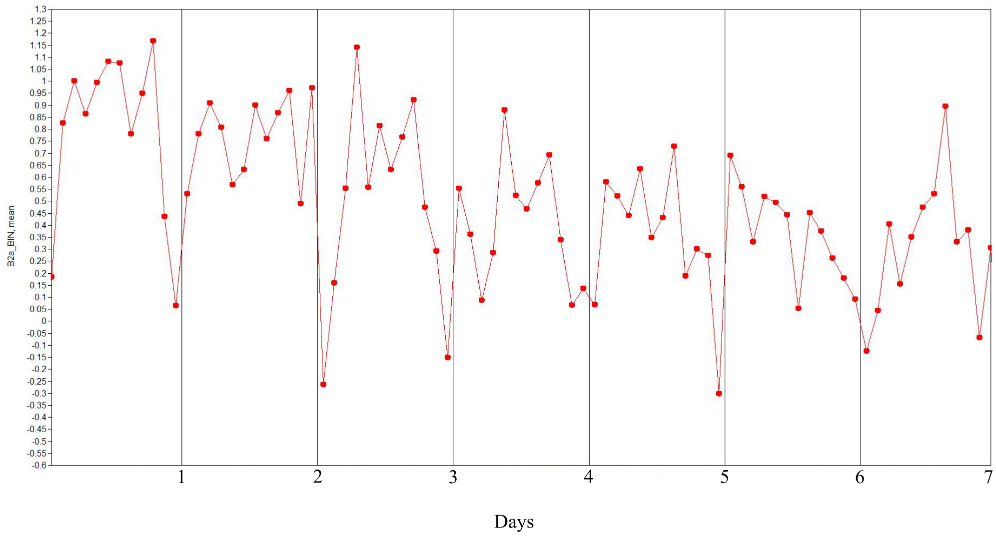
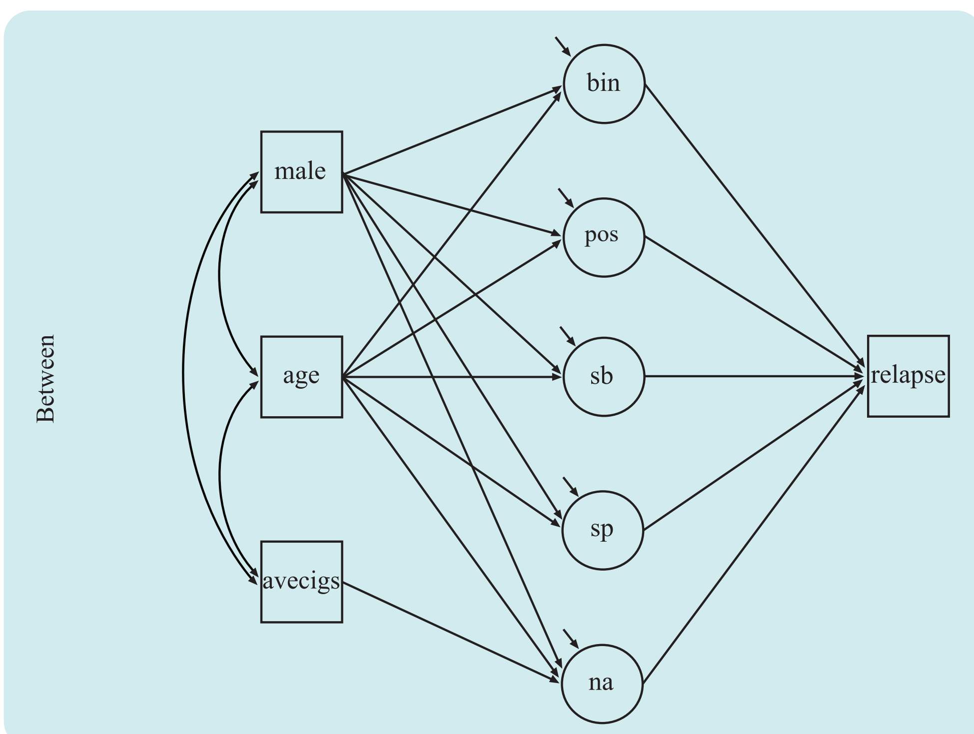


Figure 9: Between-level mediation model for two-level two-part RDSEM of smoking urge related to negative affect, time, and relapse



relapse. Having taken the trends into account, the auto-regressions for the binary and positive parts are now strongly reduced to 0.395 and 0.184, respectively (not shown in the table).

Table 6 shows the corresponding analysis using the regular approach that ignores the floor effect. It is found that smoking urge is significantly influenced by only average number of cigarettes. In contrast, the two-part analysis found significant effects also for gender (on craving intensity) and age (on craving likelihood). The random slope for the trend is significantly influenced by average number of cigarettes where the positive coefficient implies a less negative trend, that is, heavier smokers' craving declines less quickly. In contrast, the two-part analysis did not find any significant predictor. Both the regular and two-part analyses found that the relapse outcome is significantly influenced by the random intercept for smoking urge, but the two-part analysis attributes this specifically to the intensity of urges when they occur, and not to the likelihood of occurring, whereas the regular analysis does not make this distinction. The regular analysis also found a significant effect for the slope of the trend. The regular analysis shows an indirect effect from the average number of cigarettes via the random intercept to the relapse outcome while the two-part analysis shows an indirect effect from gender. No direct effect is found in the regular analysis whereas the two-part analysis found a direct effect for age. All in all, the two-part and regular analyses lead to quite different conclusions.

5 Discussion

This paper suggests that two-part modeling may provide a solution to the common problem of floor effects. It can avoid potential biasing effects due to ignoring the floor effect with the standard use of linear models with assumptions suitable for normally distributed outcomes. It can also provide a more detailed description of the relationships between the outcome and covariates allowing different covariate effects for being at the floor or not and the value above the floor. For example, in the smoking data, we observed that gender does not affect the likelihood of having a non-zero urge, but does affect the intensity of non-zero urges once they occur. The models presented represent only a small subset of possible dynamic structural equation models that are available in the Mplus implementation. In addition to the RDSEM models with a contemporaneous effect between smoking urge and negative affect that were presented, cross-lagged effects can be modeled. This could be important for inferring causal direction, and could have practical clinical utility by identifying precursors of strong urges that smokers could attend to trigger preventive actions. It is also possible to expand the use of random effects to variances, covariances, and auto regressive coefficients, allowing individual variation in these parameters as well. For example, the within-level variance of the positive part of the two-part model may be quite different across individuals. Latent variables measured by multiple indicators fit into the general modeling framework as well and provides a way to focus on factors behind the items of the measurement instrument.

It is of interest, however, to carefully consider the general applicability of two-part modeling and alternative approaches to dealing with floor effects. In the smoking urge

(2015) and Nguyen et al. (2015) but is not applied here.

Table 5: Two-part RDSEM of smoking urge related to negative affect, time, and relapse: Standardized between-level results

	Estimate	Posterior S.D.	95% C.I. Lower 2.5%	Upper 2.5%	Significance
BIN ON					
MALE	0.007	0.127	-0.243	0.256	
AGE	0.376	0.045	0.275	0.447	*
AVECIGS	0.199	0.040	0.119	0.276	*
POS ON					
MALE	-0.340	0.142	-0.614	-0.057	*
AGE	0.078	0.049	-0.021	0.173	
AVECIGS	0.085	0.046	-0.006	0.174	
NEGAFF ON					
MALE	-0.010	0.137	-0.280	0.254	
AGE	0.061	0.048	-0.034	0.154	
AVECIGS	0.089	0.044	0.003	0.174	*
SB ON					
MALE	-0.246	0.154	-0.543	0.064	
AGE	0.102	0.053	-0.005	0.205	
AVECIGS	0.066	0.051	-0.033	0.165	
SP ON					
MALE	-0.245	0.152	-0.534	0.056	
AGE	-0.020	0.053	-0.125	0.083	
AVECIGS	0.088	0.050	-0.011	0.184	
RELAPSE ON					
BIN	0.277	0.139	-0.010	0.528	
POS	0.229	0.107	0.013	0.431	*
NEGAFF	0.100	0.096	-0.090	0.288	
MALE	-0.089	0.188	-0.456	0.281	
AGE	-0.141	0.067	-0.274	-0.010	*
AVECIGS	0.110	0.057	-0.002	0.221	
SB	0.083	0.143	-0.196	0.356	
SP	0.140	0.126	-0.108	0.385	

Table 6: Regular RDSEM of smoking urge related to negative affect, time, and relapse: Standardized between-level results

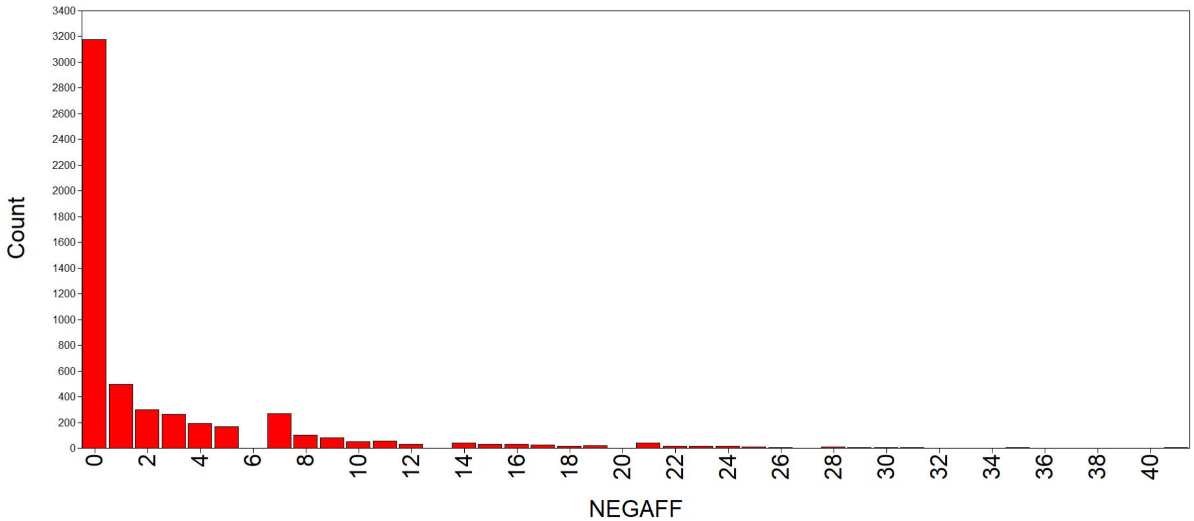
	Estimate	Posterior S.D.	95% C.I. Lower 2.5%	Upper 2.5%	Significance
URGE ON					
MALE	-0.227	0.135	-0.499	0.039	
AGE	0.071	0.048	-0.026	0.164	
AVECIGS	0.159	0.044	0.070	0.242	*
NEGAFF ON					
MALE	-0.005	0.133	-0.267	0.257	
AGE	0.059	0.048	-0.041	0.150	
AVECIGS	0.087	0.043	0.006	0.168	*
S ON					
MALE	-0.116	0.144	-0.402	0.165	
AGE	-0.041	0.050	-0.138	0.057	
AVECIGS	0.130	0.047	0.035	0.221	*
RELAPSE ON					
URGE	0.316	0.099	0.113	0.495	*
NEGAFF	0.091	0.100	-0.105	0.283	
MALE	-0.117	0.189	-0.468	0.270	
AGE	-0.104	0.071	-0.240	0.036	
AVECIGS	0.097	0.058	-0.016	0.213	
S	0.235	0.114	0.007	0.453	*

application with individuals who are trying to quit smoking, one can argue that two-part modeling is suitable not only in that the no-urge category is so frequently used, but also because the no-urge category represents a special state of having no urge to smoke at all despite being newly abstinent. Those who do have an urge to smoke are in a separate state with values typically quite a bit larger than zero. In the histogram of Figure 1, while 43% are at the floor of zero, only 6% have a value of 1 and the median value among those who have an urge is 5. This is consistent with accounts of smoking cessation experience that emphasize the episodic or 'phasic' nature of craving and the role of situational cues, over the expectation that craving would be 'tonic,' if driven by nicotine withdrawal (Ferguson & Shiffman, 2009). One can argue that to some extent, this is analogous to the medical care expenditures example of Duan et al. (1983) where not needing medical care and needing medical care represents different states and once you are in medical care, few have small expenditures.

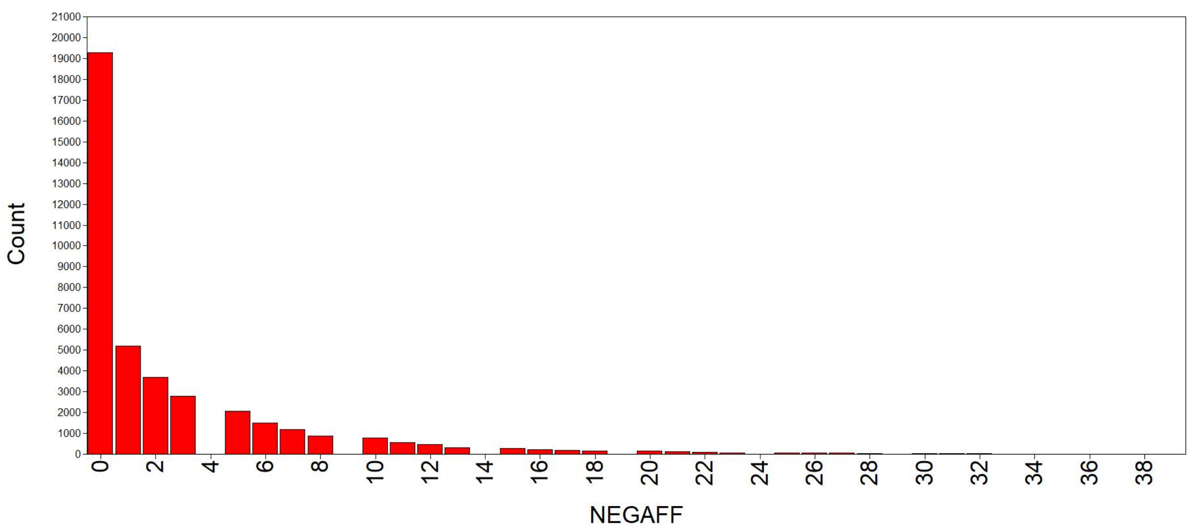
A common example of floor effects in intensive longitudinal data is seen in studies of mood with measures of negative affect where a strong floor effect is often obtained depending on the population being sampled. Two examples are considered here. The first example is provided by a study designed to detect at-risk mood profiles related to depression in adolescents (see, e.g., de Haan-Rietdijk et al., 2017 and Dietvorst et al., 2021). Experience Sampling Method (ESM) questionnaires measuring positive and negative affect were administered to 240 Dutch adolescents ages 12 to 16. Several measures per day were collected for seven days. Negative affect was measured as the sum of six 7-category items, sad, unhappy, disappointed, angry, nervous, irritated (this is notably different than the measure in Shiffman et al, 1977, which also encompassed positive emotional states). Figure 10 (a) shows that 58% of the respondents are at the floor value, reporting absence of all of those six negative feelings. The next three scale points have percentages of 9, 5, and 5. The second example is provided by data from the older cohort of the Notre Dame Study of Health and Well-being (see, e.g., Wang et al., 2012) with 56 daily measures for 270 individuals ages 51 to 91. Negative affect was measured as the sum of ten 5-category negative affect items (with positive item again absent). Figure 10 (b) shows that 48% of the respondents are at the floor value, reporting "not at all" for all ten items. The next three scale points have percentages of 13, 9, and 7. The two examples show that the positive part also has a floor effect but since it is only 9% and 13%, it most likely has little biasing effect on the two-part modeling. Two-part modeling of negative affect regressed on a set of key covariates using the DSEM model of Figure 4 finds that different covariates are significant in the binary and positive parts for the younger sample but not for the older sample.

In the context of outcomes such as negative affect, however, a key question is if the two-part assumption of two different processes, one regression for the binary and another for the positive part, is relevant. Does the floor value really represent a separate state from the positive values or is there a single process with continuously diminishing values? One can argue that two-part modeling is relevant simply because the dominance of the absence of negative affect warrants a special treatment of absence/presence. In fact, one could dichotomize the variable and analyze it as a binary outcome, but the degree of negative affect among the remaining 42% and 52% in the two negative affect examples are presumably worth investigating as well. On the other hand, if a single process is more relevant, would two-part modeling give misleading results in the sense that regression coefficients would be significant for one part but

Figure 10: Negative affect histograms



(a) 58% at the floor



(b) 48% at the floor

not the other? Also, if a single process is more relevant, how should it be modeled?

To consider the issue of one versus two processes, a Monte Carlo simulation experiment was carried out where outcome data were generated as a censored normal distribution with censoring from below resulting in a 50% floor effect and a right tail similar to those of Figure 10. A covariate was generated so that the outcome before censoring followed a linear regression. As in the earlier Monte Carlo study, a sample size of 200 was used with 50 timepoints. Although the data were generated as a single process, they were analyzed by the two-part model of Figure 4 allowing different regressions for the binary and positive parts. It was found that there was similarly high power to reject zero regression coefficients for both parts. The standardized values for the two parts were also very close. This limited investigation suggests that two-part modeling would not lead the analyst astray but may be able to inform about whether two processes are needed.[8] This topic, however, warrants further research. With regard to measures of affect, the question is also related to theoretical postulates about the nature of affect. Some theorists argue that negative affect and positive affect are opposite poles of a single dimension, so the absence of negative affect implies the presence of positive affect. That is, there may not be any binary aspect to affect measures. Conversely, many argue that negative affect and positive affect are different dimensions, so an absence of negative affect is truly an absence, and does not necessarily imply the presence of positive affect. These assumptions affect how affect is measured, and affect the relevance of two-part models.

The use of bi-polar scales to capture negative affect as in the current study can be examined further. A bi-polar scale essentially includes positive items to cover the left end of the negative affect scale. If there is a floor effect for a negative affect variable with only negative items, such as the two examples just described, can one think of those individuals as having a degree of positive affect? Assuming that the negative and positive items measure two different factors that are moderately correlated, such factors may have different antecedents. If this is the case, it makes sense that individuals at the floor of a sum of negative affect items could have covariate effects different from those above the floor, motivating the two-part modeling.

Several other approaches to handling floor effects have been proposed. One is censored-normal modeling which represents the single-process idea (see, e.g., Muthén et al., 2016). The single-process idea can also be approached by building on distributions other than the normal such a gamma and exponential distributions (for examples, see, e.g., Haqiqatkhah et al., 2023). Mixture modeling represents the two-process idea where there is a mixture at the zero floor value such that it is observed with probability 1 for one latent class of individuals and with non-zero probability for a second latent class of individuals. The latent class membership has a different regression on covariates than the regression of the outcome for the second latent class. Censored-inflated modeling (Muthén et al., 2016) also represents the two-process idea. A comparison of two-part and mixture modeling regression is discussed in Deb and Trivedi (2002). Muthén et al. (2016) compares two-part, mixture, censored, and censored-inflated regression.

Still other modeling approaches are possible. In both of the negative affect examples, the outcome is created from a set of individual items. Although these items have strong floor effects as well, they can be used as multiple indicators of a factor or

[8] 20% of the Monte Carlo replications did not converge which may be another indication of the data needing only one process.

factors that themselves can be assumed to be normally distributed, thereby making the linear-normal assumptions for the regression of factors on covariates reasonable. Given that each item has a strong floor effect, often stronger than the total, it is also possible to dichotomize each item as 0/1 and report the count of how many items have 1. This, however, leads to count modeling which has not yet been developed for Bayesian analysis of intensive longitudinal data of the general kind discussed here.

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6 Appendix

This appendix shows the Mplus inputs for the three analyses by two-part models reported in the paper. The input excerpt on this page contains the first few lines which are omitted in the three inputs but applies to all of them. Mplus Version 8.11 or later is recommended for the analyses. The Table 3 analysis cannot be done in earlier versions.

Table 1: Mplus input: beginning lines

```
DATA :          FILE = Muthen2c.dat;

VARIABLE:       NAMES = subject timeqd1-timeqd6 Day Time
                ObsType Status Urge Craving Negaff Arousal
                Gender Age Avecigs Addicted Mintofir RelapDay;

                ! ObsType=0 Random
                ! ObsType=1 Temptation
                ! ObsType=2 Lapse

                ! Status=0 Abst
                ! Status=1 Lapsed

                ! Gender=0 Female
                ! Gender=1 Male

                MISSING = ALL(999);
```

Table 2: Mplus input excerpts for the Section 4.1 two-level two-part RDSEM model

	USEVARIABLES = gender age avecigs negaff bin pos ObsType1 ObsType2; CATEGORICAL = bin; CLUSTER = subject; LAGGED = negaff(1) bin(1) pos(1); TINTERVAL = timeqd6(0.08333); WITHIN = ObsType1 ObsType2; BETWEEN = gender age avecigs;
DEFINE :	IF (ObsType==1) THEN ObsType1=1 ELSE ObsType1=0; IF (ObsType==2) THEN ObsType2=1 ELSE ObsType2=0;
DATA TWOPART:	NAMES = urge; BINARY = bin; CONTINUOUS = pos; CUTPOINT = 1; TRANSFORM = none;
ANALYSIS:	TYPE = TWOLEVEL; ESTIMATOR = BAYES; PROCESSORS = 2; BITERATIONS =(2000);
MODEL:	%WITHIN% bin pos ON negaff obstype1 obstype2; bin^ ON bin^1; pos^ ON pos^1; negaff^ ON negaff^1; %BETWEEN% bin pos negaff ON gender age avecigs; bin pos negaff WITH bin pos negaff;
OUTPUT:	STANDARDIZED TECH1 TECH4 TECH8;
PLOT:	TYPE = PLOT3; FACTORS = ALL(50);

Table 3: Mplus input excerpts for the Section 4.2 crossclassified two-part RDSEM model

	USEVARIABLES = gender age avecigs negaff bin pos ObsType1 ObsType2 ; CATEGORICAL = bin; CLUSTER = subject t; LAGGED = negaff(1) bin(1) pos(1); TINTERVAL = timeqd6(0.08333 t); WITHIN = ObsType1 ObsType2; BETWEEN = (subject) gender age avecigs; ! cna;
DEFINE:	IF (ObsType==1) THEN ObsType1=1 ELSE ObsType1=0; IF (ObsType==2) THEN ObsType2=1 ELSE ObsType2=0;
DATA TWOPART:	NAMES = urge; BINARY = bin; CONTINUOUS = pos; CUTPOINT = 1; TRANSFORM = none;
ANALYSIS:	TYPE = CROSSCLASSIFIED; ESTIMATOR = BAYES; PROCESSORS = 2; BITERATIONS =(5000);
MODEL:	%WITHIN% bin pos ON negaff obstype1 obstype2; bin^ ON bin^1; pos^ ON pos^1; negaff^ ON negaff^1; %BETWEEN T% bin pos negaff; %BETWEEN SUBJECT% bin pos negaff ON gender age avecigs;
OUTPUT:	STANDARDIZED RES TECH1 TECH4 TECH8;
PLOT:	TYPE = PLOT3; FACTORS = ALL(50);

Table 4: Mplus input excerpts for the Section 4.3 two-level two-part RDSEM model with trend, relapse, and mediation

```
                 USEVARIABLES = gender age avecigs negaff bin pos
                 relapse ObsType1 ObsType2 t;
                 CATEGORICAL = bin relapse;
                 CLUSTER = subject;
                 LAGGED = negaff(1) bin(1) pos(1);
                 TINTERVAL = timeqd6(0.08333 hrs);
                 WITHIN = ObsType1 ObsType2 t;
                 BETWEEN = gender age avecigs relapse;

DEFINE:          IF (relapDay gt 0)THEN relapse=1 ELSE relapse=0;
                 t = (hrs-168)/100;
                 IF(hrs gt 168) THEN t = 0;
                 IF (ObsType==1) THEN ObsType1=1 ELSE
                 ObsType1=0;
                 IF (ObsType==2) THEN ObsType2=1 ELSE
                 ObsType2=0;

DATA TWOPART:    NAMES = urge;
                 BINARY = bin;
                 CONTINUOUS = pos;
                 CUTPOINT = 1;
                 TRANSFORM = none;

ANALYSIS:        TYPE = TWOLEVEL RANDOM;
                 ESTIMATOR = BAYES;
                 PROCESSORS = 2;
                 BITERATIONS =(5000);

MODEL:           %WITHIN%
                 sb | bin ON t;
                 sp | pos ON t;
                 negaff ON t;
                 bin pos ON obstype1 obstype2;
                 bin^ pos^ ON negaff^;

                 bin^ ON bin^1;
                 pos^ ON pos^1;
                 negaff^ ON negaff^1;

                 %BETWEEN%
                 bin pos sb sp negaff on gender age avecigs;
                 relapse on bin pos sb sp negaff gender age avecigs;
```