ANALYZING POLICY CAPTURING DATA USING STRUCTURAL EQUATION MODELING FOR WITHIN-SUBJECT EXPERIMENTS (SEMWISE)

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Abstract

We present the SEMWISE (Structural Equation Modeling for Within-Subject Experiments) approach for analyzing policy capturing data. Policy capturing entails estimating the weights (or utilities) of experimentally manipulated attributes in predicting a response variable of interest (e.g., the effect of experimentally manipulated market-technology combination characteristics on perceived entrepreneurial opportunity). In the SEMWISE approach, a factor model is specified in which latent weight factors capture individually varying effects of experimentally manipulated attributes on the response variable. We describe the core SEMWISE model and propose several extensions (how to incorporate non-binary attributes and interactions; how to model multiple indicators of the response variable; how to relate the latent weight factors to antecedents and/or consequences; and how to simultaneously investigate several populations of respondents). The primary advantage of the SEMWISE approach is that it facilitates the integration of individually varying policy capturing weights into a broader nomological network while accounting for measurement error. We illustrate the approach with two empirical examples, compare and contrast the SEMWISE approach with multi-level modeling (MLM), discuss how researchers can choose between SEMWISE and MLM, and provide implementation guidelines.

Key words: Structural Equation Modeling; Within-Subject Experiments; Multi-level data; Policy Capturing; Conjoint Analysis.

Organizational researchers often want to determine which pieces of information most strongly influence preferences or decisions (Aiman-Smith, Scullen, & Barr, 2002). Such questions can be addressed through policy capturing designs. Policy capturing designs are in essence within-subject experiments that test how different combinations of attribute levels of stimuli influence individuals' responses. Policy capturing (also known as conjoint analysis) has been used in hundreds of judgment and decision-making studies in a variety of disciplines, including entrepreneurship, strategy, marketing, and organizational behavior (Shepherd, Patzelt, & Baron, 2013). For instance, Grégoire and Shepherd (2012) use policy capturing to examine the influence of superficial and structural similarity between a technology and a potential target market on perceived entrepreneurial opportunity (i.e., the perceived fit of the technology with the market and its perceived feasibility). Aiman-Smith, Bauer, and Cable (2001) use policy capturing to examine the relative importance of four attributes (pay, promotion opportunities, lay-off policy and a firm's ecological rating) on potential job recruits' attraction to an organization and job pursuit intentions. Table 1 presents an overview of these and some additional examples.

The analysis of policy capturing studies can take diverse forms. While these designs were traditionally analyzed using ANOVA or regression analysis (Aiman-Smith et al., 2002), more recently multi-level modeling (MLM) has become the recommended analysis technique (Aguinis & Bradley, 2014). As we argue in this paper, even though Structural Equation Modeling (SEM) is currently not being employed for analyzing policy capturing data, it could be used for this purpose. The aim of the present paper is to address this gap by introducing Structural Equation Modeling for Within-Subject Experiments, abbreviated SEMWISE.

As discussed in more detail later, the SEMWISE approach offers certain advantages over alternative methodologies in specific circumstances. In general, it provides a flexible yet rigorous analytical framework in which individually varying responses to different attributes

of experimental stimuli are modeled as latent variables. These latent variables can be easily

integrated into a broader nomological network of antecedents and consequences. Further, as

in any SEM application, detailed model fit information is available, so the specified model

can be thoroughly assessed and tested against alternative specifications, and parameter

restrictions can be easily evaluated based on indices of local misfit (e.g., modification

indices). The SEMWISE approach also allows for the use of multi-group modeling for testing

across-group measurement invariance and differences in parameters of interest. In addition,

measurement error in the response variable can be accounted for. This is important as in many

applications the response variable is latent (e.g., intention, attraction), so it may be desirable

to use multiple indicators. Finally, the SEMWISE model can account for method effects, for

instance by specifying a method factor that captures individual differences in rating scale use.

Our target audience includes researchers who (plan to) use policy capturing studies in

organizational research but were not previously aware of the fact that they could analyze their

data using SEM, as well as researchers who (plan to) use SEM but were not previously aware

of its potential to deal with policy capturing data. Although we have tried to make this

exposition of SEMWISE self-contained, some experience with SEM is probably required to

fully understand the discussion (see Kline 2016).

We will start with a simple illustrative example of a policy capturing study that

introduces the SEMWISE approach in an intuitive way. Next, we will discuss the SEMWISE

model in greater detail by first presenting the core model and then offering several model

extensions. These extensions will both show how the SEMWISE approach can deal with the

complexities that often arise in policy capturing studies and demonstrate several potential

advantages that the SEMWISE approach offers in specific situations. The empirical part of

the paper will present two applications that illustrate the method and highlight some of its

strengths. The paper ends with a comparison of the SEMWISE and multi-level modeling (MLM) approaches and guidelines on how to implement SEMWISE in practical settings.

Introductory Example

As an illustration of a SEMWISE analysis of policy capturing data, consider the fictitious example depicted in Figure 1, where participants are asked to rate four potential teammates for a quiz and the teammates are defined in terms of low vs. high warmth and competence. The researcher wants to estimate the weights (called part-worth utilities or part-worths in conjoint studies) that participants attach to teammate warmth and competence when rating the experimental profiles, where the attribute weights are inferred from the overall ratings of the profiles by decomposing the overall rating into the contribution of warmth and competence to a profile's overall rating. The way this is accomplished in the SEMWISE approach is different from the way in which it is done in the conventional regression framework, although the results are equivalent. Appendix A discusses the regression approach and its similarities and differences with the SEMWISE approach; here, we will focus on SEMWISE.

In the SEMWISE approach, a Confirmatory Factor Analysis (CFA) is specified in which the ratings of the four profiles are used as four indicators of three latent factors: an intercept factor and weight factors for warmth and competence. In contrast to a conventional CFA, each indicator is allowed to load on multiple factors (since each profile is composed of multiple attributes), and the factor loadings are fixed at particular values in order to link the overall profile ratings to the attribute levels characterizing the profiles. For instance, assuming that effect coding is used (where -1 indicates a low and $+1$ a high level on an attribute), a teammate profile with low warmth and high competence will have a loading of -1 on the warmth weight factor and a loading of $+1$ on the competence weight factor. The latent factors

are called weight factors because they are unobserved variables that represent the individually

varying weights that respondents attach to the manipulated attributes of the profiles (i.e.,

warmth and competence) when rating potential teammate profiles. In addition to the warmth

and competence weight factors, a latent intercept factor is included to model respondents'

average responses to all the profiles. The four profiles have fixed loadings of one on the

intercept factor.

In what follows, we will explain the SEMWISE specification more formally, starting

with the core model and then discussing several extensions. In Appendix A and in the general

discussion, we provide further details about the similarities and differences between MLM

and SEMWISE. Specifically, Appendix A shows how to analyze the introductory example

(Figure 1) in MLM vs. SEM, demonstrates how the models can be estimated in Mplus, and

compares the results obtained with the two methods for a simulated data set. The example

shows that the parameter estimates are the same for this basic policy capturing model,

although the terminology differs.

The SEMWISE Model

The core model

Consider a set of stimuli defined by p binary attributes of interest. Each attribute can

be absent or present (or low vs. high), and a stimulus is defined by a particular combination of

attribute levels. Using effect coding, −1 indicates the absence and +1 the presence of an

attribute. Alternatively, one could use dummy codes of 0 and +1. The levels of a stimulus on

the p attributes affect a dependent variable y, the response variable. Figure 2 displays a path

diagram and the corresponding algebraic formulation of the model for a situation where p = 3,

which (in the case of a full factorial design) results in 8 alternative stimuli representing all

possible combinations of the three binary attributes (2^3).

It is apparent that the model depicted in Figure 2 is a factor model. Though not shown in Figure 2, the factor model includes means and intercept terms (for an introduction to modeling means in SEM, see Ployhart & Oswald 2004). In contrast to the traditional factor model, all loadings are fixed at values of -1 or $+1$ (assuming effect-coding). Also, each observed variable is allowed to load on multiple factors because each profile represents a combination of attribute levels. For example, y_1 is the response to a profile in which all three attributes are present. The loading matrix links participants' observed responses to each profile (y_1 to y_8) to four latent factors: an intercept factor (η_0) and three latent weight factors (η_1 to η_3). The intercept factor has a unit loading on each observed variable and represents the average response per individual respondent; it captures true differences in average preference but also differences in scale use (i.e., rater bias). The latent weight factors represent individual differences in the weights assigned to the three attributes characterizing each profile, and these weight factors are of primary interest in policy capturing studies. Specifically, within the SEMWISE model, the means, variances and covariances of the weight factors are estimated and the weight factors can be related to other constructs, as explained below. It is therefore not necessary to explicitly compute the individual weights (i.e., factor scores).

The latent means of the weight factors η_1 to η_3 represent the average (positive or negative) contribution of each attribute (depending on whether the attribute is present or absent, or high or low) to the overall ratings across all individuals in the sample (e.g., how much high warmth adds to the overall ratings of profiles on average). The latent mean of the intercept factor η_0 captures the average response across all respondents and stimuli (and will typically be of little interest).

The variances of the weight factors represent the extent to which the individually-varying weights fluctuate about the mean of each weight factor (e.g., how much the weights attached to warmth vary across individuals); the covariances of the weight factors represent

the extent to which the weights of different factors correlate across individuals (e.g., whether individuals who value high warmth also tend to value high competence). If the variances of the latent weight factors η_1 to η_3 are close to zero, this means that the weights are homogeneous across respondents and that the random-effect specification (in which the factor scores for a given attribute are allowed to vary across respondents) reduces to a fixed-effect specification (in which the factor scores are the same for each respondent). In the same vein, a fixed intercept specification is obtained by setting the variance of the intercept factor η_0 to zero; this means that the average rating across all profiles is the same for each respondent. Of course, if the factor variances are zero, the covariances are also zero. The question of whether the effects of η_0 to η_3 ought to be specified as random or fixed effects can be addressed based on extant theory, by evaluating the confidence intervals of the variance terms in question and/or by testing model constraints on the variance terms (i.e., evaluating the deterioration in model fit when fixing the variance terms to zero by means of chi-square difference testing).

Finally, individual differences in stimulus-specific y-scores are represented by the (error) terms ε_1 to ε_8, which are assumed to have a mean of zero. These error terms can be interpreted as deviations between the ratings of a profile predicted by the model and the ratings actually observed, and the variances of the errors are generally freely estimated in the SEMWISE model.

Before the specified model can be estimated, the identification of the model has to be ascertained (see Bollen, 1989; Mulaik, 2009). General identification rules that apply to any type of SEMWISE model do not exist. However, a necessary condition for identification is that the number of unknown model parameters does not exceed the number of unique variances, covariances, and means of the observed variables (i.e., that the degrees of freedom is nonnegative). For example, for the model in Figure 2, there are 36 unique elements in the variance-covariance matrix of the observed variables and 8 observed means, and since the

number of unknown model parameters is 22 (10 factor variances and covariances, 8 error

variances, and 4 factor means), the model has 22 degrees of freedom (44 minus 22). Although

a model that satisfies the necessary identification condition is not necessarily globally

identified, the model in Figure 2 can be shown to be identified from first principles. One

characteristic of SEMWISE models that facilitates identification is that the factor loadings are

fixed to particular values. In general, policy capturing models similar to that in Figure 2 will

be identified, but for more complicated models (see below), identification has to be evaluated

on a case-by-case basis.

Once the specified model has been estimated, it can be evaluated in more detail as

follows. First, the overall fit of the model should be examined in order to assess to what extent

the model is consistent with the data (although a well-fitting model does not preclude the

possibility that other models fit the data equally well). The fit indices and suggested cutoff

values usually applied in confirmatory factor analysis can be used here (Cheung & Rensvold,

2001; Lance, Butts, & Michels, 2006). Second, even when the global fit is acceptable, it is

instructive to check indices of local misfit (residuals and modification indices) in order to

identify specific problematic model constraints. Third, researchers need to verify that the

estimated parameters are meaningful (e.g., that there are no negative variance estimates,

which can occur in more complicated models incorporating interactions among the attributes).

Finally, if the previous conditions hold, the parameter estimates can be interpreted and the

explained variance in each indicator can be examined to verify that respondents' ratings are

mainly driven by the manipulated attributes. The weight factor means, variances and

covariances can also be evaluated and, if necessary, further model restrictions and/or

extensions may be considered (e.g., weight factor variances can be restricted to zero).

In what follows, we discuss several model extensions that broaden the applicability of

SEMWISE to other designs encountered in policy capturing studies and capitalize on the

modeling capabilities offered by SEM. The extensions are not exhaustive and can be used in

combination. The Web Appendix provides Mplus syntax for generating data and Mplus,

Lavaan and Lisrel syntax for analyzing the data consistent with the core model (see Figure 2)

and most of the extensions discussed next.

Model Extensions

Model extension 1: Attributes with more than two levels

Some independent variables of interest have more than two categories or levels. Web

Appendix Example 2 presents syntax for policy capturing with non-binary attributes.

Independent variables can be metric or categorical. For metric independent variables, the

relation between the independent variable and the response variable y can be linear or

nonlinear. Linearity can be modeled by using loadings with equal intervals, such as 1, 2, and 3

if there are three equally spaced levels of the manipulated attribute (e.g., price levels of $1,

$2, and $3). Linearity can also be imposed in instances where an independent variable takes

on different levels (e.g., low, medium, high) that can be reasonably assumed to be equidistant

(so-called allocated coding; see Aiman-Smith et al., 2002). In order to model a nonlinear

relationship, a combination of fixed and freely estimated weights can be used. For example, if

respondents rate applicants with varying grades (e.g., satisfaction, distinction, and high

distinction), satisfaction could get a weight of -1, high distinction a weight of $+1$, and the

weight of distinction could be freely estimated. Finally, if the levels of an attribute are

unordered and categorical, (k-1) factors are needed to represent the information in the k

categories. For example, if the design includes products from three countries of origin (e.g.,

the U.S., Germany, and China), two weight factors are needed and the loadings for the first

(second) weight factor could be specified as $+1$, 0, and -1 (0, $+1$, and -1) for products from

the U.S., Germany, and China, respectively.

Model extension 2: Interactions between the attributes

So far we have assumed the responses are only functions of the main effects of the experimentally manipulated attributes. One can also model interactions between attributes by adding latent factors that represent combinations of attribute levels of different factors. Operationally, the loadings for an interaction factor equal the product of the loadings of its constituent effects (as in regression analysis). For example, if the interaction between attributes 1 and 2 were added to the model in Figure 2, the loadings would be +1, −1, −1, +1, +1, −1, −1, +1, and an additional weight factor η_4 would be added to the model. Three-way or even higher-order interactions can also be included by multiplying the loadings of the factors involved in the interaction. Of course, the interpretation of interactions becomes increasingly complex as more higher-order terms are added to the model. In addition, since such models have fewer degrees of freedom, various estimation problems can occur in models containing high-order interactions (e.g., negative error variances).

Some results in terms of the number of parameters to be estimated for different designs are summarized in Table 2. This table also provides important input for assessing model identification, because the degrees of freedom in an identified model cannot be negative. If all possible main and interaction effects are included in the model, the model is saturated and can exactly reproduce the data (without testing anything), so that the error variances can be fixed at zero. If mean, variance and covariance parameters associated with higher order interaction factors are near zero, then simpler models containing fewer interactions should be entertained. For reasons of parsimony, we will henceforth focus on models with only main effects. However, in some research contexts, interactions are of theoretical interest, in which case they should be included in the model. Furthermore, if the fit of the model is poor and if the main effects explain only a small portion of the variance in observed responses, it may be necessary to consider interaction factors.

Model extension 3: Multiple indicators for the dependent variable

Sometimes, the response variable in policy capturing experiments is best conceptualized as a latent variable, so researchers may want to use multiple indicators to measure it (e.g., Aiman-Smith, Bauer, & Cable 2001). Using multiple indicators for the profile ratings makes it possible to better account for measurement error in the ratings, so that attenuation due to measurement error can be corrected for within the model. Also, the use of multiple measurement methods enables researchers to separate method variance from substantive variance, in line with the multitrait-multimethod tradition (Lance, Noble, & Scullen, 2002).

This approach is illustrated in Figure 3 for a model with four main effects and eight stimuli; the Web Appendix (see example 3) provides the corresponding syntax (including parameter restrictions that make this model identified). As an example, respondents could rate the attractiveness of experimentally manipulated teammate descriptions on a five-point scale (variables y_1 to y_8 in Figure 3) as well as by means of a continuous slider scale (variables z_1 to z_8 in Figure 3). As can be seen in Figure 3, the two ratings for each profile together load on a first-order factor (the η-factors). The first-order factors then act as latent indicators of the weight factors (the ξ factors), which are now second-order factors, but otherwise the interpretation is the same as in a single-indicator model. At the same time, as can be seen on the right-hand side of Figure 3, all ratings using the same format also load on a method-specific intercept factor (see M_y and M_z in Figure 3), which we will simply refer to as method factors. A method factor is generally defined as a latent variable assumed to contribute to the variability of a set of observed response variables that share a common method (Weijters, Baumgartner, & Schillewaert, 2013). The method factors capture the average rating that each respondent gives to the entire set of profiles in a given scale format; this includes the average preference as well as individual format-specific scale use (i.e., rater bias) (Maydeu-Olivares &

Coffman, 2006). Integrating a multi-indicator measurement model into the policy capturing model is something that cannot be done in the standard MLM framework.

Model extension 4: Adding antecedents and consequences of the weight factors

A common type of research question in policy capturing research pertains to explaining individual differences in the weight or importance of attributes (e.g., Grégoire & Shepherd 2012). In MLM the consideration of potential determinants of individually varying weights results in cross-level interactions between the experimentally manipulated attributes characterizing each profile (at level 1) and the individual difference variable of interest (at level 2). In SEMWISE, the effects of individual difference variables are modeled as antecedents of the weight factors. Referring back to our introductory example (see Figure 1), to test whether respondents' need for achievement affects the weight they attach to warmth and competence in evaluating potential teammates, respondents' need for achievement could be added as an antecedent of the weight factors for warmth and competence.

A similar approach can be used for nominal antecedents. For instance, in our introductory example (Figure 1), gender might be hypothesized to influence the weights of warmth and competence in evaluating potential teammates. In SEMWISE, this could be analyzed by adding a dummy variable for gender as an observed antecedent of the weight factors (see Figure 4a and Example 4a in the Web Appendix). The regression weight linking the dummy variable to the weight factors would represent the gender difference in the extent to which warmth and competence affect potential teammate evaluations.

A SEMWISE model can also specify the weight factors as antecedents of subsequent outcome variables (see Figure 4b). For instance, a researcher could study entrepreneurs' risk seeking tendencies in a policy capturing design and model the weight factors as antecedents of later entrepreneurial activity in risky markets. The weight factors can also act as mediating variables (see Example 5 in the Web Appendix). There is no direct equivalent of this

approach in an MLM framework, although as an indirect approximation, one could save individual estimates of regression coefficients and use them in subsequent analyses.

Model extension 5: Multiple groups

Observed categorical variables can also be used as grouping variables. For this extension (multiple group analysis) there is no counterpart in the standard MLM framework. For instance, instead of using gender as an antecedent, respondents' gender could be used as a grouping variable, and the same SEMWISE model could be simultaneously estimated for two samples differing in gender (see Figure 4c and example 4b in the Web Appendix). In this setup, the between-group mean difference in the SEMWISE factors would capture the gender difference in the extent to which a specific attribute (e.g., warmth) affects teammate evaluations. But in addition, one could also test for between-group differences in the weight factor variances, which would indicate whether one group is more or less heterogeneous in terms of the importance assigned to a given attribute.

When combining multi-group specifications with the consideration of antecedents and consequences, the grouping variable can also be studied as a moderator of the relationship between the weight factors and the antecedents or consequences. For instance, one could investigate whether the effect of need for achievement (the antecedent) on the weights of warmth and competence in teammate choice is moderated by respondent gender (the grouping variable).

Overview of empirical applications

To illustrate the SEMWISE approach, we now report two empirical applications. First, using policy capturing data on potential teammate preferences, we illustrate the core SEMWISE model (cf. Figure 2), as well as an extension with an observed antecedent used either as a covariate (cf. Figure 4a) or as a grouping variable (cf. Figure 4c). Second, we use policy capturing data on organizational attractiveness to illustrate models in which the

response variable is measured with multiple indicators (cf. Figure 3) and the latent weight

factors are related to latent antecedents.

Empirical application 1

The first empirical application is an illustrative policy capturing study concerning

evaluations of potential teammates. The approach was inspired by Caruso, Rahnev, and

Banaji (2009). In the current study, student participants (men and women) rated potential

teammates (all women) for a trivia game of math and science. Fictitious team member profiles

were created that vary in terms of a clearly task-relevant attribute (competence, more

specifically IQ), a possibly process-relevant attribute (perceived warmth), and an irrelevant

attribute (facial attractiveness). When evaluating potential teammates, above average IQ is

expected to be valued in a teammate because it increases the chances of winning (Caruso et

al., 2009). Warmth, although offering less of a direct competitive advantage, could be

functional in terms of facilitating trust and mutual coordination (Cuddy, Glick, & Beninger,

2011). Facial attractiveness is presumably irrelevant to the task at hand, but it is plausible that

mate selection preferences for attractive faces developed through evolution will influence

men's (although possibly not women's) teammate preferences (Fink & Penton-Voak, 2002).

Method

We constructed eight profiles using a full factorial design in which we experimentally

manipulated attractiveness (below vs. above average), warmth (low vs. high) and competence

(average vs. high IQ). All experimental profiles depicted white women. For each experimental

profile, we constructed a profile description by randomly sampling a female name, a (low vs.

high) warmth description, and an (average vs. high) IQ level from the appropriate pool of

elements (e.g., an attractive picture with a low-warmth description and high IQ level), using

the form "[Picture]. [Name] is described by her friends as [warmth level]. She has an IQ of [IQ level]." The specific levels were sampled from the sets of elements shown in Table 3.

Thus, each respondent saw a series of different profiles for which the name, picture and warmth description were never identical (IQ levels could coincidentally replicate, but not systematically so). This approach was intended to make the task less transparent and more involving, and to present participants with stimuli sampled from a broader domain. As a potential side-effect, it is likely to increase random variation in responses, but the SEMWISE model explicitly accounts for this (in the residual terms for each of the eight responses).

The experimental profiles were shown one per page, in randomized order. We added a replication profile to test participants' consistency; this ninth profile was the same for all respondents (except for the name), but again did not verbally or visually replicate any of the other profiles and corresponded to an above average attractiveness, low warmth, high competence profile. The correlation between the ratings for the two replicated profiles was $r = .60$, which suggests reasonable consistency (especially in light of the random sampling of the elements making up the profile).

Participants rated each profile on a visual scale using stars with a continuous range from 0 to 5. To get acquainted with the task, participants had to give three ratings in line with the following instructions: "To get acquainted with the question format, please rate the profiles below in line with the instructions (by selecting a score from zero to five stars): (1) Person A has all the rights skills and the right personality. Give this profile a very high score. (2) Person B is average. Give this profile an intermediate score. (3) Person C does not have the right skills and not the kind of personality you are looking for. Give this profile a very low score." To be able to proceed to the next page, respondents had to give a rating above 3 for person A and a rating below 3 for person C.

We collected data from students at a U.S. university, retaining for analysis only those respondents who indicated English as their native language (because the personality descriptions were verbally demanding) and White/Caucasian as their race (to avoid potential confounding effects of respondent sex and race). In our sample, N = 260, ages range from 19 to 21 years (M = 19.4, SD = .55), and 46.9% of participants are women. Appendix B reports the correlation matrix.

Results

The design of this study corresponds to the core SEMWISE model presented in Figure 2. The baseline model shows acceptable fit to the data (χ^2 (22) = 41.864, p = .006, RMSEA = .059, CFI = .972, TLI = .965, SRMR = .058). The percentage of explained variance in the eight profile ratings ranges from .52 to .63 (all p < .001). The weight factor means and variance terms (and their associated standard errors) are reported in Table 4 and are all significantly different from zero. Correlations between the weight factors are all non-significant, with the exception of the correlation between warmth and competence (r = -.29, p < .01). These results indicate that competence, warmth and facial attractiveness all contribute (positively) to teammate preferences, despite the irrelevance of facial attractiveness for the task at hand. Also, there is individual variation in the weight assigned to each of the attributes. Finally, participants who attach more weight to competence tend to attach less weight to warmth.

Adding covariates as a determinant of the weight factors is one way of trying to better understand the individual variation in the weight factors. We estimate a SEMWISE model using participants' gender (FEMALE; 0 = male, 1 = female) as a covariate. This model corresponds to the SEMWISE extension with an observed antecedent used as a covariate (cf. Figure 4a) and it shows acceptable fit to the data (χ^2 (26) = 43.915, p = .015, RMSEA = .051, CFI = .975, TLI = .965, SRMR = .053). The effect of FEMALE on the attractiveness weight

factor is negative but not statistically significant (B = -.049, SE = .030, t = -1.625, p = .104). None of the other weight factors is significantly related to FEMALE either (all p > .40). Furthermore, when controlling for participants' gender, the correlation between the warmth and competence weight factors remains significantly negative (r = -.29, p < .01).

To further investigate gender differences in team member evaluation, we run a two-group SEMWISE model, using participants' gender as the grouping variable. This approach corresponds to the model extension depicted in Figure 4c. The model shows acceptable fit to the data (χ^2 (44) = 67.156, p = .014, RMSEA = .064, CFI = .968, TLI = .960, SRMR = .067). The parameter estimates are reported in Table 5.

This analysis yields some additional results that cannot be obtained from the previous model (where FEMALE was a covariate, not a grouping variable) nor from a multilevel analysis. In general, gender differences are small, but some differences between men and women are of note. First, the mean of the attractiveness weight factor is significant among men (M = .079, t = 3.424, p = .001) but not among women (M = .034, t = 1.753, p = .080); however, the difference between the two means is not significant (t = 1.494, p = 0.135). In addition, the variance of the attractiveness weight factor is significant among men (Var. = .025, p < .01) but not among women (Var. = .002, p = .730); this difference between the two variances is statistically significant (t = 2.051, p = .040). In sum, for male participants facial attractiveness has a small but statistically significant effect on teammate preferences on average, although there are significant individual differences in the magnitude of this effect across men. In contrast, for female participants facial attractiveness does not have a significant effect on average, and there is little variation in this effect across women. We also find that the negative correlation between the weight of warmth and the weight of competence found in the sample as a whole only holds for men (r = -.45, p = .001), not for women (r = -.14, p = .298), although the difference in the magnitude of the correlation is not

significant (Wald $\chi^2(1)$ = 3.218, p = .073). This finding suggests that men may have a stronger tendency to focus either on warmth or on competence (but not both) when evaluating potential female teammates.

Empirical application 2

For the second empirical application, we collected data using multiple indicators for the response variable. Similar to Aiman-Smith et al. (2001), we use policy capturing to examine the relative influence of four factors (two job factors of pay and promotion, and two organizational image factors of lay-off policy and ecological rating) on potential job recruits' attraction to an organization.

Method

We designed company profile descriptions by manipulating the same four attributes as Aiman-Smith et al. (2001), but specifying only two levels for each attribute. Specifically we generated eight profiles in a fractional factorial design as reported in Table 6. Respondents judged organizational attractiveness based on each profile using two items: (a) 'To what extent would you like to work for this company?' (rated by manipulating a sliding bar linked to a smiley face with five levels ranging from 1= low to 5=high) and (b) 'How attractive do you find this company?' (rated by means of a continuous sliding scale marked by five stars with scores ranging from zero to five). These formats were chosen because they are visually attractive and engaging for respondents, and they also are different from the Likert scales we used for other variables. The profiles were presented in randomized order to all respondents. The eighth profile was presented twice (and included in the randomized profile sequence) to test the internal consistency of the policy capturing responses. The correlation between the responses to the two replicated profiles (using a two-factor model with two items per factor

and specifying unit loadings) was r = .66 ($p < .001$), which suggests that respondents' ratings were reasonably consistent.

Respondents also answered a six-item scale on Environmental Concern (EC), adapted from Catlin and Wang (2012), in which half the items were reverse-scored: I would describe myself as environmentally responsible; I consider the potential environmental impact of my actions when making many of my decisions; I am concerned about wasting the resources of our planet; My habits are not affected by environmental concerns (reversed); Environmentally friendly actions are too inconvenient for me (reversed); I'm not particularly bothered by worries about our environment (reversed). Finally, a shortened 10-item version of the Impression Management (IM) scale (Paulhus, 1991) was included to control for socially desirable responding. This scale also consists of a mix of reversed and non-reversed items.

We collected data from students at a U.S. university. In our sample, N = 276, age ranges from 18 to 36 (M = 19.6, SD =1.9), and 44.9% are women. Appendix C reports the correlation matrix of all study variables.

Results

To illustrate the integrated use of a measurement model with rating scale format method factors, we run a SEMWISE model corresponding to the one shown in Figure 3. For each of the eight focal profiles (i.e., not including the replicated profile), we specify one factor with two indicators. For each of these eight factors, the first indicator has a unit loading on the underlying factor for purposes of identification; the loading of the second indicator is constrained to be equal across all eight factors (as there is no reason why the same scale should be less reliable for certain profiles than others). These first-order factors (η_1 to η_8) serve as the SEMWISE indicator variables of the second-order weight factors (ξ_1 to ξ_4) with loadings fixed depending on the attribute levels contained in a profile, as listed in Table 6. To capture scale usage effects for the two scale formats, we specify two method factors, M_y and

M_z, one for each scale format, which freely correlate with each other and with the weight factors ξ_1 to ξ_4 (correlations between factors are not shown in Figure 3 for readability). The indicator intercepts are fixed to zero, but the means of the method factors are freely estimated (as are the means of the weight factors ξ_1 to ξ_4). The method factor means represent the average scale response for each of the two formats and they capture both individuals' scale usage (rater bias) and average attractiveness perceptions. The resulting model shows acceptable fit to the data ($\chi^2(100) = 144.174$, $p = .003$, RMSEA = .040, CFI = .983, TLI = .980, SRMR = .047). Percentage of explained variance ranges from .75 to .88 for the y-indicators and from .76 to .87 for the z-indicators. Means, variances, and correlations of the four weight factors are reported in Table 6. All weight factors have statistically significant means and variances, indicating that compensation, promotion, layoff policy and a company's environmental concern all affect organizational attractiveness, although the two job factors (pay and promotion) are on average more important than are the two organizational image factors (relating to lay-off policy and a firm's ecological rating). Also, respondents who attach more weight to promotion tend to attach less weight to a company's layoff policies ($r = -.40$, $p < .05$) and environmental concern ($r = -.32$, $p < .05$). The means for the two method factors are $M_y = 2.752$ (SE = .027) and $M_z = 2.309$ (SE = .035), with a correlation of $r = .765$ (SE = .034). The method factors do not show significant correlations with the weight factors, with the exception of a correlation between M_y and the layoff policy factor, $r = .265$ (SE = .125, $p = .034$).

Next, we add two latent variables: EC is included as an antecedent of the SEMWISE weight factors, and IM is added as a control variable. The goal of this extension is twofold. First, it illustrates how the SEMWISE model can be easily integrated into a broader nomological network. Second, it allows us to validate the assumption that policy capturing designs (especially the environmental concern weight factor) are less vulnerable to social

desirability than self-reports based on direct questioning (in this case, the EC scale) (Tomassetti, Dalal, & Kaplan, 2016). This is especially relevant for environmental concern, which, because of its moral connotations, is likely to be susceptible to the influence of socially desirable responding (Jones & Willness, 2013).

We start with a preliminary confirmatory factor analysis (CFA) of the latent covariates Environmental Concern (EC) and Impression Management (IM). Both scales contain reversed items (reversed items were not reverse-scored), and we include a method factor M_x to control for individual variation in scale usage (Maydeu-Olivares & Coffman, 2006; Weijters et al., 2013); all indicators, irrespective of wording direction, have unit loadings on the method factor, whereas the loadings on the substantive factors are freely estimated (so the loadings for regular and reversed items are expected to have opposite signs). For the sake of parsimony and model fit (and since our focus is not on the measurement parameters of this scale but the structural estimates), we use four item parcels for IM (two parcels based on the reversed items and two based on the non-reversed items; Rhemtulla, 2016). The resulting CFA model (with parcels for IM and with a method factor) fits the data well ($\chi^2(33) = 42.645$, RMSEA = .033, CFI = .985, TLI = .980, SRMR = .042). The method factor has a variance term significantly different from zero (p < .001), and omitting the method factor results in a significant deterioration in fit ($\Delta\chi^2 (1) = 27.61$, p < .001).

Next, we specify EC and IM as antecedents of the weight factors, as shown in Figure 5. For readability, the figure does not contain factor correlations, but the following sets of factors are allowed to covary: (a) the three method factors M_x, M_y, and M_z, where the only significant correlation is the one already found in the core model, between M_y and M_z ($r = .77$, SE = .03, p < .001); (b) the weight factors compensation (COMP), promotion (PROMO), Layoff policy (LAYOFF) and the company's environmental concern (CEC) (as already discussed in the core model); and (c) EC and IM, which have a significant positive

correlation of r = .18 (SE = .08, p = .033). The resulting model fits the data well: $\chi^2(280)$ =

299.744, p = .200; RMSEA = .016, CFI = .994, TLI = .993, SRMR = .047. The only

significant regression weight linking the SEMWISE weight factors (COMP, PROMO,

LAYOFF and CEC) to EC and IM is the one between EC and CEC, with standardized

B = .83 (SE = .07, p < .001). Thus, those who are high on self-rated environmental concern

actually assigned a greater weight to a company's environmental record when indicating their

attraction to a company. Interestingly, CEC is not significantly related to IM (Standardized

B = −.13, SE = .10, p = .197). The results provide support for the convergent validity of the

CEC factor, as it is strongly related to individuals' EC, although—interestingly—the CEC

weight factor is less affected by IM than is the EC scale. This is consistent with the recent

finding by Tomassetti et al. (2016) that policy capturing is more resistant to socially desirable

responding than traditional self-report techniques.

Discussion

In the current paper, we introduced SEMWISE (Structural Equation Modeling for

Within-Subject Experiments) and demonstrated how it can be used for analyzing policy

capturing data. To give credit where credit is due, we want to stress that the proposed

approach constitutes a specific application of the more general principle posited by Curran

(2003), who stated that "[a]ny two-level linear multilevel model can be estimated as a

structural equation model given that this is essentially a data management problem" (p. 557).

This equivalence between MLM and SEM is commonly capitalized on in latent curve

modeling, where repeated observations over time are nested within individuals and where the

use of SEM is well established (Feingold, 2009). Whereas MLM uses time as an independent

variable in such instances, latent curve models based on SEM incorporate time as fixed values

within the factor loading matrix (Curran, 2003). Within-subject experimental designs,

including policy capturing designs, constitute a similar data structure, in that repeated

measurements are related to fixed experimental variables (the manipulated attributes). Thus,

here too the fixed values for the experimental manipulations can either be included as

independent variables in a multilevel model or as fixed values of the factor loading matrix in

an SEM.

Two important questions need some further elaboration and will be addressed in more

detail now. First, what are some practical guidelines for implementing SEMWISE? Second,

when should researchers stick with Multi-Level Modeling (MLM), and when might they want

to opt for SEMWISE instead?

Application guidelines

With regard to the first question, the empirical applications can serve as examples for

researchers who want to apply a similar approach. More generally, we suggest the stepwise

approach shown in Figure 6. As a first step, we propose starting with the core model (without

antecedents or outcomes) while accounting for multi-group and/or multi-indicator data from

the start and deciding how to specify the measurement parameters of the model (i.e., loadings,

second-order factor structure if applicable, and residual variances). In a second step, the

resulting model needs to be carefully evaluated, returning to step one if necessary. A third

step involves including interaction terms if required. In a fourth step, the variances of the

weight factors are evaluated, so that antecedents, correlates and/or outcomes can be added for

those weight factors that show significant variation between individuals, and if applicable,

parameters are tested for across-group invariance. The final step involves interpretation and

reporting.

We did not encounter issues with model non-convergence or improper estimates,

neither in our empirical applications nor our simulations (see Web Appendix). If researchers

do run into such problems, we recommend two things. First, model identification needs to be

verified. The models presented in the current paper are all identified and the Web Appendix

provides syntax including constraints required for identification. For a more detailed

discussion of model identification, we refer to chapter six in Mulaik (2009). Second, if the

model is identified but still results in improper estimates, we recommend using Bayesian

estimation with minimally informative prior distributions, which strongly facilatates

convergence without inducing bias, as recently demonstrated by Helm et al. (2017).

Choosing between MLM and SEMWISE

The primary objective of this paper is to demonstrate the potential of the proposed

SEMWISE approach. To be clear, the goal is not to question the usefulness of MLM for

analyzing policy capturing data. Table 7 summarizes the main similarities and differences

between MLM and the SEMWISE approach as applied to policy capturing. In common policy

capturing studies, the SEMWISE and MLM approaches will lead to the same results. To

demonstrate this equivalence, Appendix A contains syntax for generating a dataset in

accordance with the stylized policy capturing example considered earlier (Figure 1) and for

analyzing the data using both SEM and MLM. The resulting parameter estimates are identical.

However, the setup of the data file, the specification of the model, and the labeling of the

parameters are all different (see Appendix A). A prime consideration in choosing between

MLM and SEMWISE therefore will often relate to a researcher's familiarity with and/or

preference for MLM versus SEM. As a rule, the MLM and SEM approaches for analyzing

policy capturing data are equivalent for data from a single group of respondents, using a

single indicator per profile, where no outcomes are related to the weights. Since such

instances are quite common, MLM is a good choice for many policy capturing studies. For

instance, MLM is well suited for analyzing the examples from the literature mentioned in the

introduction and in Table 1. That being said, SEMWISE offers some interesting modeling

possibilities that future policy capturing researchers may want to capitalize on, primarily

related to (a) measurement, (b) model evaluation and comparison, and (c) the types of hypotheses that can be tested.

Related to measurement, research on organizational and managerial behavior has long been characterized by a strong emphasis on scale construction and measure validation, in which Confirmatory Factor Analysis and Structural Equation Modeling have played an important role (Edwards, 2001; Hinkin, 1998). The SEMWISE approach can facilitate the same measurement rigor in policy capturing research. In the core model (Figure 2), each profile rating has a residual variance term, which captures a mix of random measurement error, method effects, and profile-specific variance. The residual variance term specification is flexible, in that residual variances can be allowed to differ across profiles and residual correlations could be included if there are reasons for doing so, for instance if profiles are shown in a fixed sequence and order effects occur. A more sophisticated measurement model is offered by the multi-indicator model (Figure 3), where residual terms are estimated at two levels: The indicators (the profile ratings) have residual terms that capture the variance that remains (presumably consisting mostly of random error variance) after accounting for profile-specific and method-specific effects, and the first-order factors (η_1 through η_8 in Figure 3) have residual terms that capture variance not accounted for by the weight factors (after accounting for scale-specific method effects).

Second, in terms of model evaluation and comparison, SEM offers a well-established framework for evaluating model fit (Mulaik, 2009). This is helpful for comparing alternative models (e.g., models containing more or less restrictive residual variance specifications), but also when evaluating a single model in isolation, where a good model fit suggests that the observed data are consistent with a given theoretical model (even though it is possible that other models may fit even better or equally well). In the case of policy capturing studies, good model fit supports the assumption that the ratings are indeed driven by the latent weight

factors. Problematic model fit indicates that somehow the model is not in line with the observed data, which (among other things) can be due to non-modeled correlations (e.g., two profiles may have unintended similarities, or presentation order effects may be at play), or which may suggest the need to reconsider parameter restrictions (e.g., to allow for nonlinearities in the effect of an attribute on profile ratings) or include additional terms in the model (e.g., adding interaction terms to a main-effects only model).

Third, researchers may have specific modeling needs that can only be handled in a SEMWISE framework. Two important extensions in this regard are multi-group modeling and the possibility to specify more comprehensive models that include antecedents and/or outcomes of weight factors. Variance-covariance structures can be compared across multiple samples (e.g., men vs. women, across countries or organizations, etc.) by using multi-group SEM (Vandenberg & Lance, 2000). In our first empirical example, for instance, we found that the attractiveness weight factor showed greater variance among male participants compared to female participants. This illustrates how the approach facilitates across-group comparisons of model parameters other than weight factor means.

Another interesting modeling opportunity is that by adding antecedents, correlates and outcomes of the weight factors, the weight factors can be embedded in a broader nomological network with other latent and/or observed variables. In this way, policy capturing weight factors could be used as mediating variables. To illustrate, consider a variation on the first empirical application, where men vs. women (the antecedent) would be compared in terms of the weight they attach to the physical attractiveness of candidates (i.e., the mediating weight factors). These weights could then act as antecedents of outcomes of interest, such as biased selection choices or evaluations. Similarly, entrepreneurs from different countries or from different industries (antecedent) might attach different weights to social control or other

characteristics of strategic alliances (i.e., the mediating weight factors), which could in turn predict engagement in alliances differing in duration and goal realization (outcome).

In sum, SEMWISE may be preferable to multilevel analysis in some situations, including the following: (a) the dependent variable is latent (e.g., attractiveness, performance ratings) and researchers want to correct for measurement error and method variance in the data (e.g., related to the use of particular rating scale formats); (b) researchers want to carefully evaluate their model specification and/or examine alternative model specifications in terms of fit with the data; and (c) the model of interest entails across-group comparisons of parameters other than weight means (e.g., variance terms of weight factors) and/or the examination of nomological networks involving other constructs, in which the weight factors serve as antecedents or mediating variables of outcomes of interest.

Concluding Remarks

SEMWISE is a method for analyzing data collected in a policy capturing study. The design of the study will usually not require adaptation, and we refer to excellent review-based tutorials on how to set up policy capturing studies, including Aiman-Smith et al. (2002), Karren and Barringer (2002) and Aguinis and Bradley (2014). Researchers planning to use the SEMWISE approach may want to spend some extra thought on the use of multiple indicators for the profile ratings. If researchers want to explicitly model method factors, it is recommended that they measure the response variable with several different formats. In the second empirical example, we used two indicators (a smiley face format and a five-star rating). Future research may want to explore which types of formats perform best in terms of respondent motivation and data quality.

In certain types of policy capturing studies, researchers who plan to use SEMWISE may deem it beneficial to limit the number of profiles presented to respondents to reduce respondent burden and leave more opportunity for measuring other variables, specifically

when the goal is to study a broader nomological network surrounding the weight factors. In such instances, we recommend that researchers first consult in more detail sources that discuss tradeoffs related to presenting a small versus a large numbers of profiles (Aiman-Smith et al., 2002; Graham & Cable, 2001; Sauer, Auspurg, Hinz, & Liebig, 2011). Advanced users could adapt the syntax provided in Appendix A for running Monte Carlo power analyses to determine the appropriate number of profiles and/or respondents (Muthén & Muthén, 2002).

The focus of the current paper is on using SEM for analyzing policy capturing data, but—as implied by the name given to the approach—its applicability is broader. To illustrate, some of the studies reported in Table 1 are not policy capturing studies in the narrow sense, in that the experimental stimuli are not fully defined by the experimental attributes and may contain additional random variation (Reb & Cropanzano, 2007) and/or idiosyncratic elements included to enhance the realism of the stimuli (Rosman, Lubatkin, & O'Neill, 1994). Furthermore, some within-subject experiments do not require participants to rate profiles, but may use a different type of dependent variable. For instance, Rosman et al. (1994) present two types of lenders (commercial vs. venture capital lenders) with hypothetical loan cases and subsequently register the types of information the lenders search for on their computers in response to each loan case. The total amount of financial information and the total amount of strategic information acquired then serve as two dependent variables. As another example, within-subject experiments in which physiological responses to manipulated stimuli are obtained could also be analyzed with the types of models proposed here. For such within-subject experiments, as for policy capturing data, the earlier mentioned advantages and disadvantages of the SEMWISE approach apply under the same conditions as we discussed there.

Limitations of the SEMWISE approach include the following. First, even though we did not encounter this in our empirical applications, it is plausible that for complex models fitted to small samples, convergence and (empirical) identification issues might arise. In such instances, if it is not possible to increase the sample size, it might be useful to revert to multilevel regression modeling or to impose some simplifying assumptions (e.g., restraining selected weight factor variances to zero). Future research needs to investigate to what extent such problems occur and how they can be resolved. Second, on a more pragmatic level, data management, data analysis, and interpretation of the results in a SEMWISE framework may be nonstandard and initially challenging, especially for non-SEM users. Whether the additional effort is justified will depend on researchers' familiarity with SEM and the specifics of the research question at hand. At any rate, we hope that the SEMWISE approach opens new opportunities for researchers.

Appendix A

Comparison of the SEMWISE and MLM analysis approaches

This appendix compares the SEMWISE and multi-level modeling (MLM) approaches in terms of data setup, data analysis, and (interpretation of) results as applied to the stylized example shown in Figure 1 of the main text. Figure A1 shows how the data file is structured in the MLM approach (left-hand panel) compared to the SEMWISE approach (right-hand panel), using the four responses of the fictitious respondent in Figure 1 in the main text as an example.

Multilevel data setup

Respondent	Profile	Profile warmth	Profile competence	Rating
1	1	1	-1	2
1	2	-1	1	4
1	3	1	1	5
1	4	-1	-1	1
2	1	...	...	...
2	2	...	...	...
...	...	...	...	...

SEMWISE data setup

Respondent	Rating for profile 1	Rating for profile 2	Rating for profile 3	Rating for profile 4
1	2	4	5	1
2	...	...	...	...
3	...	...	...	...

Figure A1. Data setup in a simplified policy capturing study.

As shown in Figure A1, in the MLM dataset, respondents' reactions to the four profiles (obtained by crossing the two levels of warmth with the two levels of competence) are specified on four separate lines of data (i.e., each line represents the rating of one profile, with multiple lines for each respondent). In addition, the profile attribute levels are represented by two additional variables, one containing the effect-coded attribute levels for warmth for each profile, the other containing the effect-coded attribute levels for competence for each profile. The profiles' attribute levels are repeated across respondents, but the ratings are respondent-specific. For the SEMWISE approach, each participant has one line of data and there are four columns of ratings corresponding to the ratings of the four profiles. In other words, MLM requires data in long format, SEMWISE requires data in wide format. In

the SEMWISE approach, the attribute levels of the profiles are not part of the dataset but are specified as fixed model parameters in the analytical model (see the loadings in Figure 1).

In the MLM approach, the ratings of the teammate profiles are regressed on each profile's warmth and competence level, where (for the sake of this example) effect coding is used to represent the profiles (i.e., −1 represents a low level, +1 represents a high level of an attribute). The estimated regression coefficients are the weights (or utilities) that respondents attach to warmth and competence, which are inferred from the overall ratings of the profiles. In other words, the overall rating of a profile is decomposed into the weights of the attribute levels that characterize the profile. It can be shown that when using MLM, the estimated regression coefficients, which are allowed to vary across respondents, are a compromise between (or weighted combination of) two types of regressions, a pooled regression and individual-level regressions (Gelman & Hill, 2007). In a pooled regression, it is assumed that all respondents assign the same weights to warmth and competence when rating teammates, so the regression coefficients are fixed to be equal across respondents. In an individual-level regression, it is assumed that each respondent assigns idiosyncratic weights to warmth and competence when rating teammates, so a separate regression equation is estimated for each respondent across the rated profiles (four in the present case). If there is little variability in coefficients across respondents, the MLM estimates will be close to the pooled estimates, but as the variability in coefficients across respondents increases, the MLM estimates move toward the individual-level estimates. The advantage of the MLM regression coefficients is that, on the one hand, the limiting assumption of effect homogeneity is relaxed and that, on the other hand, the estimates tend to be more stable than the individual-level regression coefficients (which are often based on a relatively small number of distinct profiles).

In the SEMWISE approach, the estimated weights are the same as in the MLM approach, but the way in which the model is specified and the weights are estimated is quite different. Instead of regressing teammate ratings on warmth and competence, one specifies a

factor model in which the ratings of the four experimental profiles are treated as the observed

indicators of three latent factors: an intercept factor, a weight factor for warmth, and a weight

factor for competence. In order to estimate a factor model, the data have to be structured

differently, as shown in Figure A1.

Although the SEMWISE model is a factor model, it should be noted that the

SEMWISE factor model differs from a conventional factor model in that the factor loadings

are fixed to particular values (analogous to the effect-coded independent variables in the

MLM approach) and each indicator (i.e., each profile rating) loads on multiple factors, the

reason being that each profile rating is assumed to be a function of the conjoint effect of

multiple weight factors (e.g., the rating of the profile with high warmth and high competence

depends on the weight that respondents attach to warmth and the weight that respondents

attach to competence).

The weight factor scores in the SEMWISE approach are identical to the regression

coefficients estimated in the MLM approach. Specifically, the latent intercept factor captures

the average rating that each respondent gives to the entire set of profiles. The latent intercept

factor has unit loadings on the four indicators (the ratings of the four profiles) and

corresponds to the intercept term in the MLM approach. The four profile ratings have

loadings on the latent warmth and competence weight factors, and these loadings correspond

to the profiles' effect codes (for warmth and competence) in the MLM approach. Thus, both

approaches model each profile rating as a function of its effect-coded attribute levels and the

respective weights (regression coefficients in MLM, weight factor scores in SEMWISE) of

these attribute levels. Since the loadings are effect-coded as -1 for low and $+1$ for high

warmth and competence, respectively, twice the estimated factor score is the difference in the

weight attached to low and high warmth or competence.

Below we provide Mplus syntax to simulate data corresponding to the example shown

in Figure 1 and to analyze the data in an equivalent way using either SEMWISE or MLM

(see Figure A1). The Mplus output shows that the parameter estimates are the same across the

MLM and SEMWISE analyses, although the terminology differs across approaches.

1. Data generation

```
TITLE: Data generation for SEMWISE vs. MLM (Fig 1 and Fig A1);
MONTECARLO:
NAMES = y1-y4;                          !response variables: profile rating;
NOBS = 250;                             !sample size
SAVE = example_wide.dat;                !generated data filename
SEED =  0;                              !results can be replicated exactly
MODEL POPULATION:                       !true model for data generation
icept  BY y1-y4@1;                       !intercept factor
wfwarm BY y1@1 y2@-1 y3@1 y4@-1;        !weight factor for warmth
wfcomp BY y1@-1 y2@1 y3@1 y4@-1;        !weight factor for competence
icept*.7 wfwarm*.7 wfcomp*.7;           !factor variances are .7
icept WITH wfwarm*.1;                    !factor covariance
icept WITH wfcomp*.1;                    !factor covariance
wfwarm WITH wfcomp*.1;                   !factor covariance
y1-y4*.2;                               !residual variance of response
variable
[y1-y4@0];                              ! intercepts of response variable
[icept*3 wfwarm*.6 wfcomp*.3];          !intercept and weight factor means
MODEL: y1-y4 with y1-y4;                !observed sample covariances
```

2. Data analysis using the SEMWISE approach

```
TITLE: SEMWISE analysis for the example in Figures 1 and 2;
DATA: FILE = example_wide.dat;         !use the data in wide format
VARIABLE: NAMES = y1-y4;               !response variables
MODEL:
icept  by y1-y4@1;                      !intercept factor
wfwarm by y1@1 y2@-1 y3@1 y4@-1;       !weight factor for warmth
wfcomp by y1@-1 y2@1 y3@1 y4@-1;       !weight factor for competence
[y1-y4@0];                             !response intercepts are set to zero
[icept wfwarm wfcomp];                 !freely estimated factor means
y1-y4(e);                              !residual variances equal for
correspondence with MLM
OUTPUT: TECH1 STANDARDIZED;            !standardized keyword gives R²
```

3. Data analysis using the MLM approach

```
Title: Multilevel modeling (MLM) analysis for Figures 1 and 2;
data: file = example_wide.dat;
DATA WIDETOLONG:
   WIDE = y1-y4 | W1-W4 | C1-C4;
   LONG = y | xwarm | xcomp;
   IDVARIABLE = person;
   REPETITION = profile;
VARIABLE: names = y1 y2 y3 y4;
          usevar = W1 W2 W3 W4 C1 C2 C3 C4 y xwarm xcomp person;
          AUXILIARY = W1 W2 W3 W4 C1 C2 C3 C4;
cluster = person;
within = xwarm xcomp;
DEFINE:
  W1 =  1;
  W2 = -1;
  W3 =  1;
  W4 = -1;
  C1 = -1;
```

```
   C2 =  1;
   C3 =  1;
   C4 = -1;
 analysis: type =  random twolevel;
          estimator = ml;
 model:
 %within%
 wfwarm | y on xwarm;
 wfcomp | y on xcomp;
 %between%
 wfwarm wfcomp;
 y;
 wfwarm with y;
 wfcomp with y wfwarm;
```

4. Selected output for both approaches

SEMWISE					MLM				
	Est.	S.E.	t	p		Est.	S.E.	t	p
					Between Level				
WFWARM WITH					WFWARM WITH				
ICEPT	0.138	0.049	2.815	0.005	Y	0.138	0.049	2.819	0.005
WFCOMP WITH					WFCOMP WITH				
ICEPT	0.118	0.048	2.451	0.014	Y	0.118	0.046	2.565	0.010
WFWARM	0.136	0.049	2.788	0.005	WFWARM	0.136	0.054	2.497	0.013
Means					Means				
ICEPT	3.036	0.055	55.193	0.000	Y	3.036	0.055	55.192	0.000
WFWARM	0.545	0.055	9.855	0.000	WFWARM	0.545	0.055	9.854	0.000
WFCOMP	0.294	0.055	5.364	0.000	WFCOMP	0.294	0.055	5.363	0.000
Variances					Variances				
ICEPT	0.707	0.068	10.434	0.000	Y	0.707	0.066	10.661	0.000
WFWARM	0.715	0.069	10.442	0.000	WFWARM	0.715	0.065	10.992	0.000
WFCOMP	0.700	0.067	10.426	0.000	WFCOMP	0.700	0.069	10.185	0.000
Residual Variances					Within Level				
Y1	0.196	0.018	11.180	0.000					
Y2	0.196	0.018	11.180	0.000	Residual Variances				
Y3	0.196	0.018	11.180	0.000	Y	0.196	0.016	12.575	0.000
Y4	0.196	0.018	11.180	0.000					

Appendix B

Correlation matrix for empirical application 1

		1	2	3	4	5	6	7	8
1	Female								
2	HHL	.009							
3	HLL	.039	.481						
4	HHH	-.023	.420	.297					
5	HLH	-.062	.222	.376	.418				
6	LHL	.055	.547	.382	.358	.103			
7	LLL	.027	.432	.585	.280	.344	.415		
8	LHH	.043	.415	.337	.556	.337	.418	.289	
9	LLH	.045	.169	.398	.362	.595	.188	.459	.414

Note: Correlations based on data setup in wide format (responses to the experimental profiles correspond to variables 2 to 9). Female refers to respondent gender (0 = male, 1 = female). The other variable names refer to the levels (L = low, H = high) of the three attributes attractiveness, warmth and competence.

Appendix C

Correlation matrix of empirical application 2

	y1	y2	y3	y4	y5	y6	y7	y8	z1	z2	z3	z4	z5	z6	z7	z8	EC1	EC2	EC3	EC4	EC5	EC6	IM1	IM2	IM3	IM4	IM5	IM6	IM7	IM8	IM9
y2	.22																														
y3	.15	.22																													
y4	.27	.28	.23																												
y5	-.08	.22	.16	.16																											
y6	.13	.09	.12	.17	.13																										
y7	.15	.14	-.07	.17	.24	.37																									
y8	.18	.25	.08	-.07	.18	.10	.22																								
z1	.67	.30	.19	.26	.04	.12	.16	.24																							
z2	.25	.74	.25	.25	.25	.13	.14	.22	.50																						
z3	.14	.27	.69	.22	.16	.13	-.03	.09	.38	.44																					
z4	.23	.28	.22	.75	.21	.19	.15	.01	.40	.44	.38																				
z5	-.04	.17	.14	.15	.77	.17	.20	.14	.15	.37	.29	.37																			
z6	.17	.14	.19	.21	.14	.75	.31	.13	.34	.33	.40	.35	.30																		
z7	.18	.17	-.07	.17	.26	.40	.79	.24	.32	.32	.08	.30	.37	.46																	
z8	.19	.24	.13	.02	.26	.14	.24	.70	.45	.37	.30	.22	.36	.36	.40																
EC1	-.19	.05	.15	.06	.15	-.10	-.23	-.08	-.15	.04	.09	.07	.11	-.12	-.19	-.08															
EC2	-.13	.03	.18	.06	.08	-.16	-.28	-.13	-.11	.03	.09	.07	.07	-.15	-.29	-.11	.60														
EC3	-.17	.07	.13	.02	.15	-.14	-.26	-.13	-.16	.06	.06	.06	.14	-.15	-.26	-.11	.46	.48													
EC4	.03	-.15	-.18	-.18	-.18	.12	.24	.13	.04	-.11	-.10	-.16	-.15	.11	.23	.14	-.45	-.48	-.39												
EC5	.08	-.09	-.10	-.11	-.11	.09	.25	.11	.00	-.14	-.11	-.18	-.13	.08	.22	.09	-.36	-.37	-.28	.39											
EC6	.11	-.18	-.21	-.12	-.14	.18	.31	.12	.09	-.14	-.14	-.12	-.15	.14	.29	.09	-.47	-.57	-.51	.56	.46										
IM1	-.05	.04	.03	.03	.10	-.08	.02	-.03	-.09	-.04	-.03	-.03	.07	-.09	-.02	-.06	.07	.07	.12	.05	.04	-.03									
IM2	-.02	-.10	-.08	-.08	.06	.03	-.02	.01	.05	-.02	-.04	-.06	.03	.02	.07	.03	.02	-.04	-.03	-.01	-.05	.10	-.25								
IM3	-.06	.07	.08	.04	.07	.02	-.06	.01	.01	.07	.00	.03	.07	-.03	.00	.06	.16	.11	.11	-.10	-.03	-.12	-.08	.19							
IM4	.04	.02	-.02	.10	-.05	.03	-.01	-.08	.05	.02	-.07	.07	-.04	-.01	.00	.00	.00	-.09	-.01	.06	.10	.11	.15	.04	.03						
IM5	.01	-.02	.03	.05	-.04	-.04	-.01	-.06	-.04	.01	.00	.06	-.04	-.04	.03	-.03	.09	.11	.20	-.10	.03	-.07	.01	.10	.12	-.02					
IM6	.01	.03	.04	-.01	-.07	.03	.03	.03	-.03	-.03	-.03	.04	-.03	-.03	.03	.00	-.02	.07	.07	-.06	.09	-.04	.05	-.06	-.09	.07	.02				
IM7	-.05	-.07	.06	.02	-.03	.04	-.04	-.04	-.08	-.06	.06	.00	.04	.05	-.02	-.08	.04	.09	.10	.04	.04	-.06	.27	-.18	-.17	.02	.04	.13			
IM8	.02	.05	-.03	-.01	.08	-.07	.11	.09	.03	.03	-.02	-.01	.10	-.07	.09	.06	-.10	-.15	-.02	.15	.09	.17	.25	-.09	-.11	.16	.00	.04	.09		
IM9	-.03	.01	-.07	-.09	.00	-.05	.00	.06	-.01	.06	-.09	.00	.01	-.05	.04	.11	.07	.00	.12	-.01	-.07	-.03	-.13	.24	.36	-.01	.17	-.11	-.36	-.08	
IM10	-.05	-.10	.06	.00	.03	.00	-.09	-.11	-.04	-.03	.04	.04	.03	.02	-.09	-.09	.17	.22	.14	-.11	-.18	-.12	-.10	.23	.21	-.22	.27	-.04	-.02	-.01	.20

Note: Correlations based on data setup in wide format. Variables y1-y8 refer to profile ratings using the first item ('To what extent would you like to work for this company?' rated by manipulating a sliding bar linked to a smiley face with five levels ranging from 1= low to 5=high), z1-z8 to profile ratings using the second item ('How attractive do you find this company?' rated by means of a continuous sliding scale marked by five stars with scores ranging from zero to five). EC1-EC6 refer to the Environmental Concern scale items, IM1-IM10 to the Impression Management scale items.

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Table 1

Some examples of policy capturing applications

Dependent variable and type of experimental stimuli	Manipulated attributes	Source
Organizational attractiveness based on job and organization descriptions	Pay Promotion Layoff policy Ecological rating	Aiman-Smith et al. (2001)
Choice of prospective teammates for a trivia contest	Education IQ Experience Body weight	Caruso et al. (2009)
Evaluation of potential CEO successors after failure	Type of failure: competence vs. integrity Outsider, interim, insider	Connelly, Ketchen, Gangloff, and Shook (2016)
Fit and feasibility of entrepreneurial opportunities (technology-market combinations)	Superficial market-technology similarities Structural market-technology similarities	Grégoire and Shepherd (2012)
Work satisfaction as a function of fit	Person-job fit Person-group fit Person-organization fit	Kristof-Brown, Jansen, and Colbert (2002)
Organizational attractiveness based on features of organizational image	Type of company (demanding, results-oriented, detail-oriented, and innovative) Type of applicant sought (self-disciplined, conscientious, reliable, well-organized, hard-working, sharp, intelligent, brilliant, logical, and smart)	Newman and Lyon (2009)
Organizational attractiveness based on signals about organizations' diversity management (DM) approach	Value type (none specified, terminal, instrumental, dual) Acculturation strategy (neutral, assimilation, integration)	Olsen and Martins (2016)

Decision to persist with strategic alliances	Output Behavioral control Social control Competence trust Goodwill trust	Patzelt and Shepherd (2008)
Evaluations of dynamic performance of sales people	Performance trend Performance mean Performance variation	Reb and Cropanzano (2007) [a]
Strategic and financial information acquisition in assessing loan cases	Structured vs. ill-structured settings	Rosman et al. (1994) [b]
Global ratings of job performance based on aspects of performance	Employees' task performance Citizenship performance Counterproductive performance	Rotundo and Sackett (2002)
Assessment of attractiveness of entrepreneurial opportunities	Value Rarity Inimitability Impact on the natural environment	Shepherd et al. (2013)
Organizational attractiveness based on job and organization descriptions	Organization offering essential services/products to the public Opportunity to use skills and abilities Autonomy and independence Responsibility and leadership opportunities Pay and fringe benefits Flexibility in scheduling work hours and vacations	Tomassetti et al. (2016)

[a,b] = These studies are not policy capturing studies in the narrow sense: The profiles were not fully defined by the manipulated attributes since there were additional differences between the profiles. In [a], performance curves were generated based on the trend, mean and standard deviation specification, with addition of random error. In [b], each of four loan cases contained idiosyncratic elements to enhance external validity.

Table 2

Parameters as a function of number of attributes

Factorial design (number of observed variables, p)	Number of unique observed variances/covariances and means	Parameters estimated in a main-effects model (assuming distinct error variances)	Parameters estimated in a saturated model
2^2	14	13	14
2^3	44	22	44
2^4	152	36	152
2^k	$\dfrac{p(p+3)}{2}$	$\dfrac{k(k+3)}{2} + p$	$\dfrac{p(p+3)}{2}$

Note: k is the number of dichotomous experimental factors; p is the number of observed variables (responses). In the saturated model,

all possible interactions are included, but the error variances are restricted to zero.

Table 3

Stimulus construction for empirical application 1

Attribute	Element	Source/reference	Levels	Set
Attractiveness	[Picture]	Chicago Face Database (Ma, Correll, & Wittenbrink, 2015), adapted to a 160 x 112 format	below average	12 pictures of white women close to attractiveness score of 2.57 (i.e., M - 1 SD)
			above average	12 pictures of white women close to attractiveness score of 4.34 (i.e., M + 1 SD)
/	[Name]	listofrandomnames.com	N.A.	Jackelyn, Alison, Gabriele, Lorretta, Dottie, Marybeth, Sarina, Hester, Janet, Rosemary
Warmth	[warmth]	Fiske, Cuddy, Glick, and Xu (2002)	high	friendly, trustworthy, warm, good-natured
			low	not always kind, occasionally unfriendly, sometimes aloof, a bit standoffish
Competence	[IQ]	Caruso et al. (2009)	average	randomly sampled number from the range [100-104] (inclusive)
			high	randomly sampled number from the range [118-122] (inclusive)

Table 4

Parameter estimates for the one-group analysis in empirical application 1

Parameter	Weight factor	Est.	SE	t	p
Means	Intercept	2.83	.04	72.30	< .001
	Competent	.64	.02	28.95	< .001
	Warm	.50	.02	23.09	< .001
	Attractive	.06	.02	3.74	< .001
Variances	Intercept	.35	.04	10.09	< .001
	Competent	.08	.01	7.18	< .001
	Warm	.08	.01	7.03	< .001
	Attractive	.02	.01	2.64	.008

Table 5

Parameter estimates for the two-group model in empirical illustration 1

		M				F				Diff.			
		Est.	SE	t	p	Est.	SE	t	p	Est.	SE	t	p
Mean	Intercept	2.820	.052	54.696	<.001	2.849	.060	47.593	<.001	-.029	.079	-.372	.710
	Attractive	.079	.023	3.424	.001	.034	.019	1.753	.080	.045	.030	1.494	.135
	Warm	.490	.030	16.413	<.001	.504	.031	16.145	<.001	-.014	.043	-.330	.741
	Competent	.657	.029	22.757	<.001	.619	.034	18.171	<.001	.038	.045	.845	.398
Variance	Intercept	.318	.044	7.227	<.001	.394	.056	7.035	<.001	-.076	.071	-1.064	.288
	Attractive	.025	.009	2.756	.006	.002	.006	.345	.730	.023	.011	2.051	.040
	Warm	.075	.015	5.035	<.001	.076	.015	4.883	<.001	-.001	.021	-.026	.979
	Competent	.066	.014	4.754	<.001	.098	.018	5.342	<.001	-.032	.023	-1.378	.168

Note: M = men, F = women, Diff. = difference between the parameter estimates for men vs. women.

Table 6

Attributes, profiles (stimulus coding) and estimation results, empirical application 2

Attribute	Levels		Stimuli specification / Loadings								M		Var.		Correlations		
	-1	1	1	2	3	4	5	6	7	8	Est.	SE	Est.	SE	1	2	3
1. COMP: The firm's compensation package is somewhat [x] average for the industry	below	above	-1	-1	-1	1	1	1	1	-1	.48	.02	.04	.01			
2. PROMO: the typical career path for the average graduate includes [x] promotion in five years	no	one	-1	1	-1	-1	1	-1	1	1	.46	.02	.04	.01	.28		
3. LAYOFF: The company's policy is that employees are [x] laid off.	sometimes	rarely	1	1	-1	1	-1	-1	1	-1	.28	.02	.03	.01	-.01	**-.40**	
4. CEC: Concern for the environment is [x] priority in the company	not a	a	-1	1	1	1	1	-1	-1	-1	.26	.02	.05	.01	-.10	**-.32**	-.15

Note: The response variable was scaled from zero to ten. The intercept factor has unit loadings, but was not part of the cards (stimuli) presented to respondents. Correlations with $p < .05$ are printed in boldface. All mean and variance estimates are significantly different from zero ($p < .05$). COMP = Compensation; PROMO = Promotion opportunities; LAYOFF = Layoff policy; CEC = Company's environmental concern.

Table 7

Comparison of the Multilevel (Mixed) Model and the SEMWISE Approach

	Multilevel (Mixed) Model	SEMWISE Approach
Primary purpose of the analysis	To study the influence of categorical or continuous independent variables (IVs) on a dependent variable (DV) in situations in which the data have a hierarchical structure. In a within-subject design, the repeated observations are nested within respondent and the IVs are categorical. Determinants of the variation in the level-1 random coefficients can be studied in the level-2 model.	Same as in the multilevel model. Additionally, both antecedents and outcomes can be related to the weight factors (i.e., the individually varying effects of IVs on DVs).
Measurement model	No explicit measurement model for the DV or the determinants of the random coefficients in the level-2 model. If the IVs in the level-1 model are manipulations, no measurement model is needed.	It is possible to specify a factor model for the DVs if multiple indicators of each DV are available. Alternatively, unreliability of measurement can be accounted for by incorporating an external measure of reliability (e.g., coefficient alpha) into the analysis. Unreliability of measurement in the determinants and consequents of the random coefficient factors can also be modeled. Measurement quality can be assessed based on the usual statistics (e.g., composite reliability).
Assumptions about the error structure of the repeated measures	Many different error structures are possible. Model comparisons can be conducted to find the most appropriate error structure, in an effort to strike a balance between type I and type II errors.	Same as in the mixed model, although the different error structures have not been preprogrammed in existing software and have to be implemented by the researcher.
Fit assessment	Models can be compared based on information theory measures (AIC, BIC, etc.). A likelihood ratio test of whether the variances and covariances of the random effects are nonzero is also available.	All fit assessments available in mixed models can be used. Additionally, all fit indices used in structural equation modeling are available (chi-square goodness of fit test, absolute and incremental fit indices).
Variance explained	Alternative measures of variance explained are available, even though there does not seem to be a consensus on which ones to use and report; but see LaHuis, Hartman, Hakoyama, and Clark (2014)	The variance explained in each observed variable (repeated measure) is readily available. This indicates how well the experimental factors account for the variation in a profile's ratings across respondents.
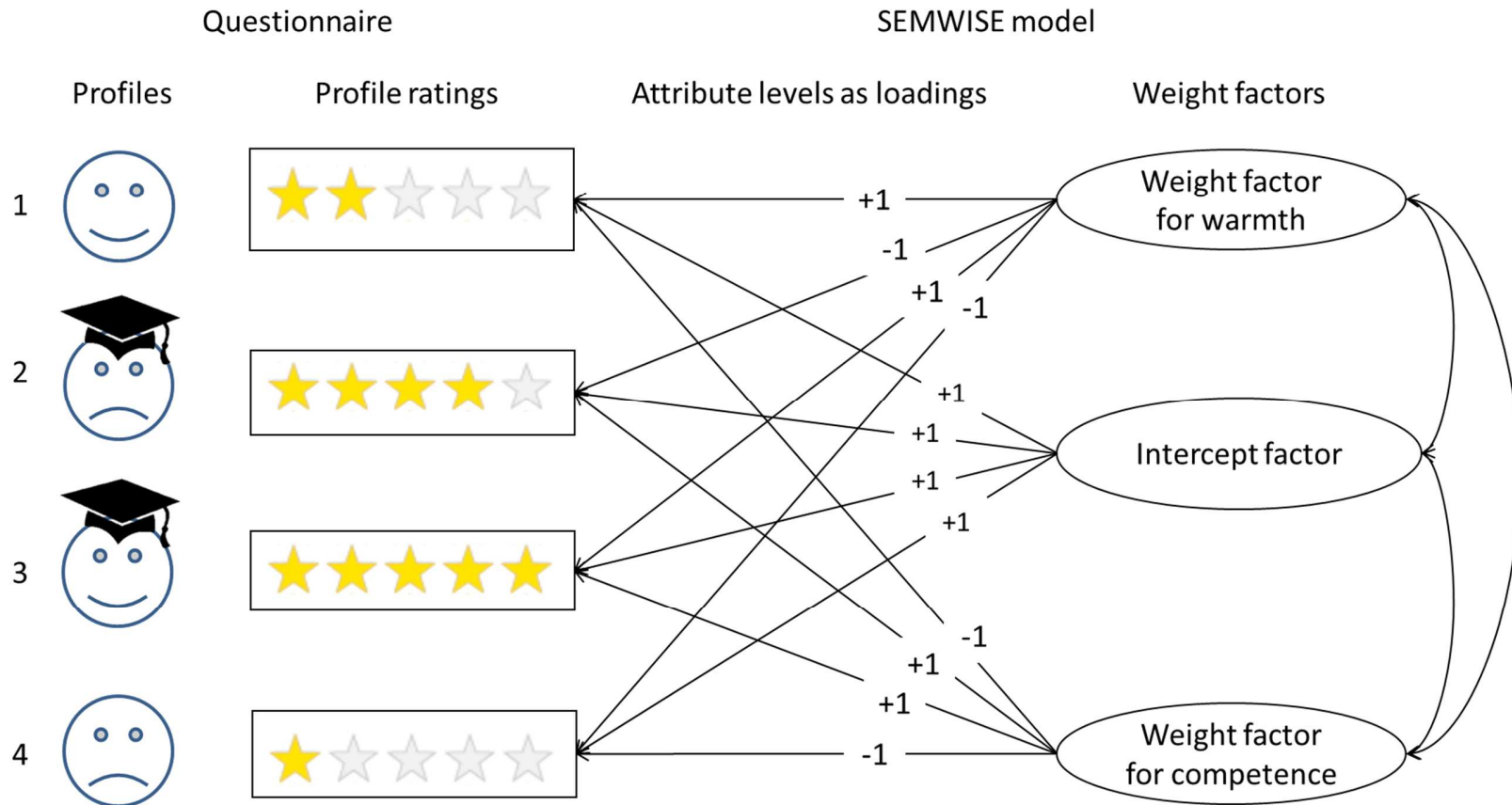
Figure 1. Stylized policy capturing example using a SEMWISE model. Respondents rate four experimental teammate profiles varying in warmth (high = smiling face vs. low = sad face) and competence (high = graduation cap vs. low = no cap) on a 5-star scale (left). In SEMWISE, these ratings are used as indicators of two weight factors plus an intercept factor (right). Since the profiles consist of combinations of warmth and competence, the profile ratings are modeled as combinations of warmth and competence weights. Respondents who value warmth (competence) will rate the first and third (second and third) profiles higher relative to the second and fourth (first and fourth) profiles, controlling for competence (warmth). The intercept factor has unit loadings for all four profiles and thus captures individuals' average ratings of the four profiles, regardless of competence and warmth.

$$\begin{bmatrix} y_1 \\ y_2 \\ y_3 \\ y_4 \\ y_5 \\ y_6 \\ y_7 \\ y_8 \end{bmatrix} = \begin{bmatrix} 1 & +1 & +1 & +1 \\ 1 & -1 & +1 & +1 \\ 1 & +1 & -1 & +1 \\ 1 & -1 & -1 & +1 \\ 1 & +1 & +1 & -1 \\ 1 & -1 & +1 & -1 \\ 1 & +1 & -1 & -1 \\ 1 & -1 & -1 & -1 \end{bmatrix} \cdot \begin{bmatrix} \eta_0 \\ \eta_1 \\ \eta_2 \\ \eta_3 \end{bmatrix} + \begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \varepsilon_3 \\ \varepsilon_4 \\ \varepsilon_5 \\ \varepsilon_6 \\ \varepsilon_7 \\ \varepsilon_8 \end{bmatrix}$$
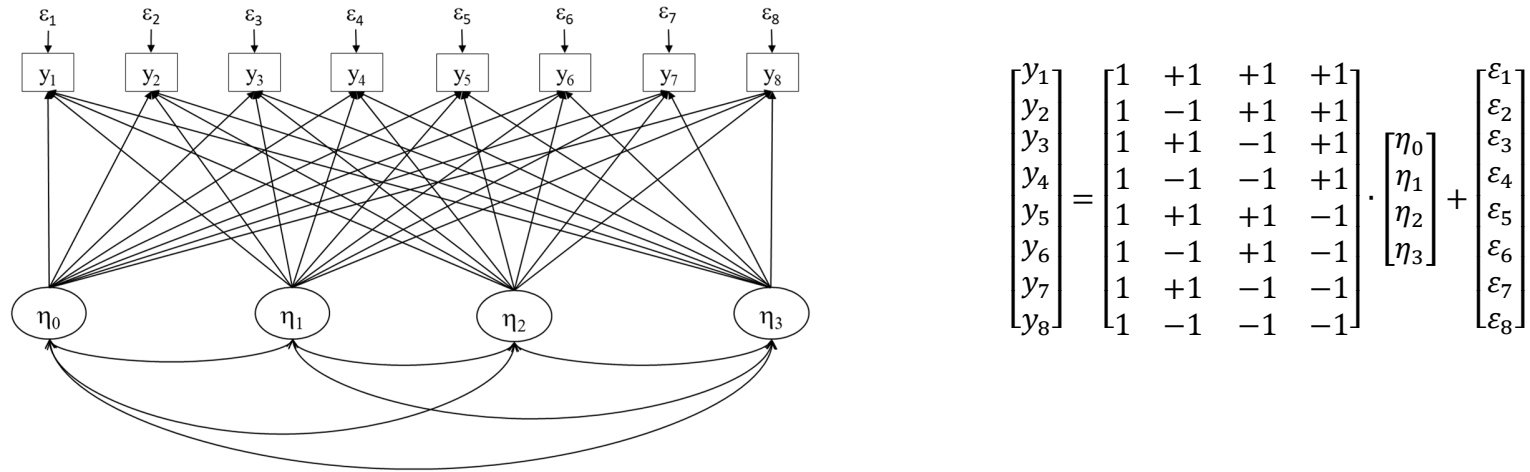
Figure 2. SEMWISE model for three binary attributes. The indicators y_1-y_8 represent individuals' ratings of the eight stimuli and load on four latent factors; the first factor (η_0) captures the mean rating across all stimuli, the other three (η_1, η_2, η_3) capture the effects of each of the three attributes. For readability, Figure 2 does not include the mean structure, which includes four factor means (the item intercepts are restricted to zero).
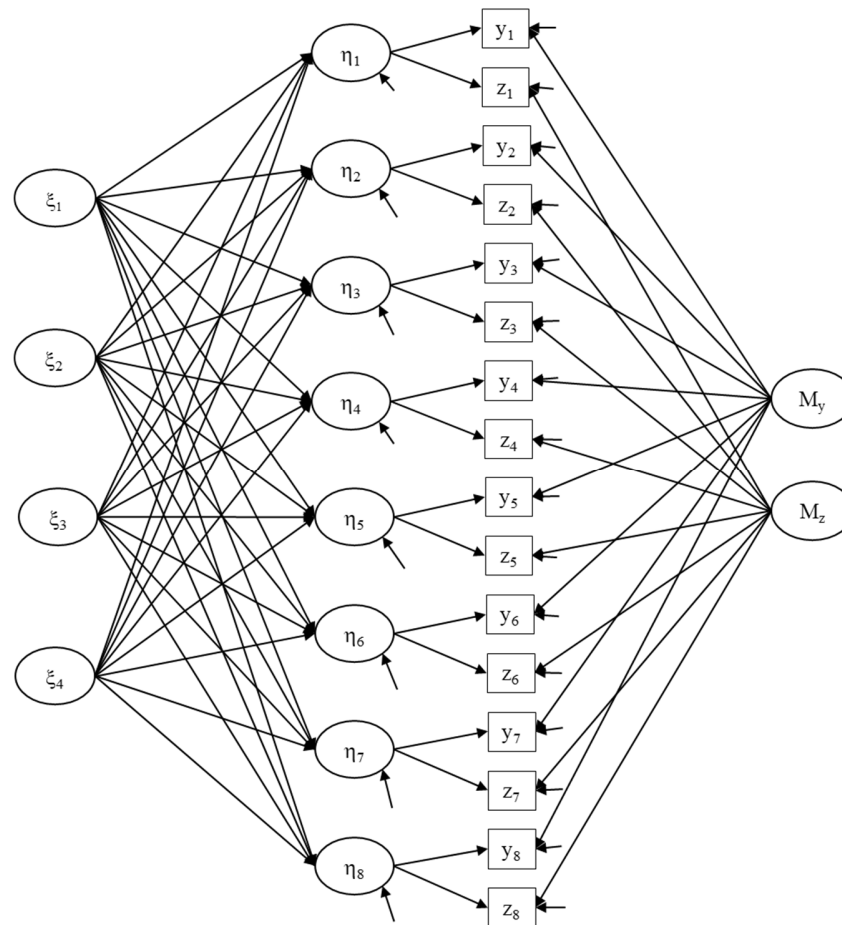
Figure 3. SEMWISE model extension with multiple indicators for the dependent variable and two method factors. Factor covariance terms are omitted for readability.

(a)   (b)   (c)

Figure 4. SEMWISE model extensions with (a) an observed antecedent variable, (b) observed outcome variable, (c) grouping variable.

Figure 5. SEMWISE model extension with latent antecedents and multiple method factors (empirical application 2). Factor covariance terms are omitted for readability.

1. Model specification. Specify the core model, accounting for the following:
   a) Grouping:
      If data are collected from different groups of respondents that need to be compared, specify the grouping variable and
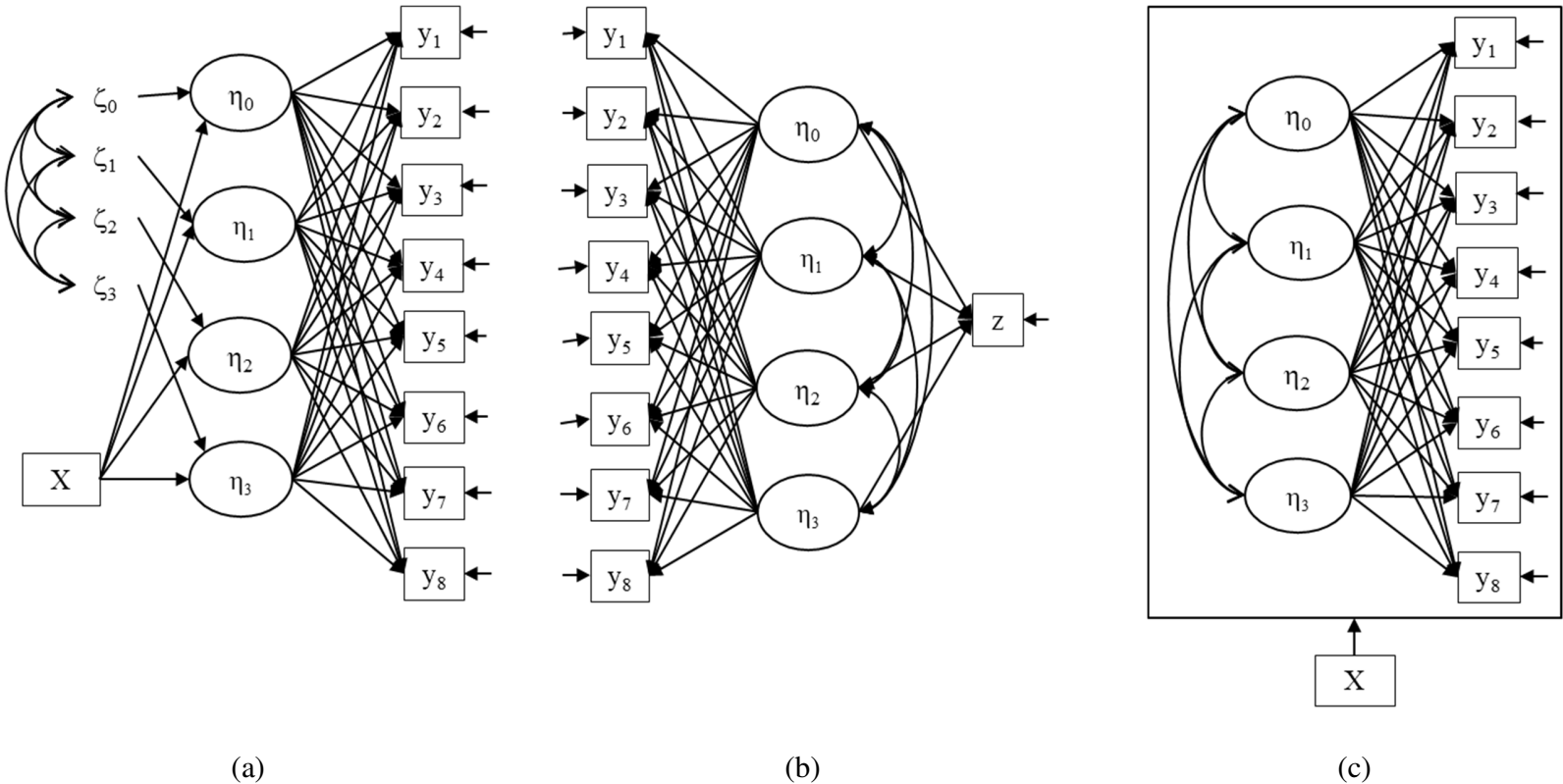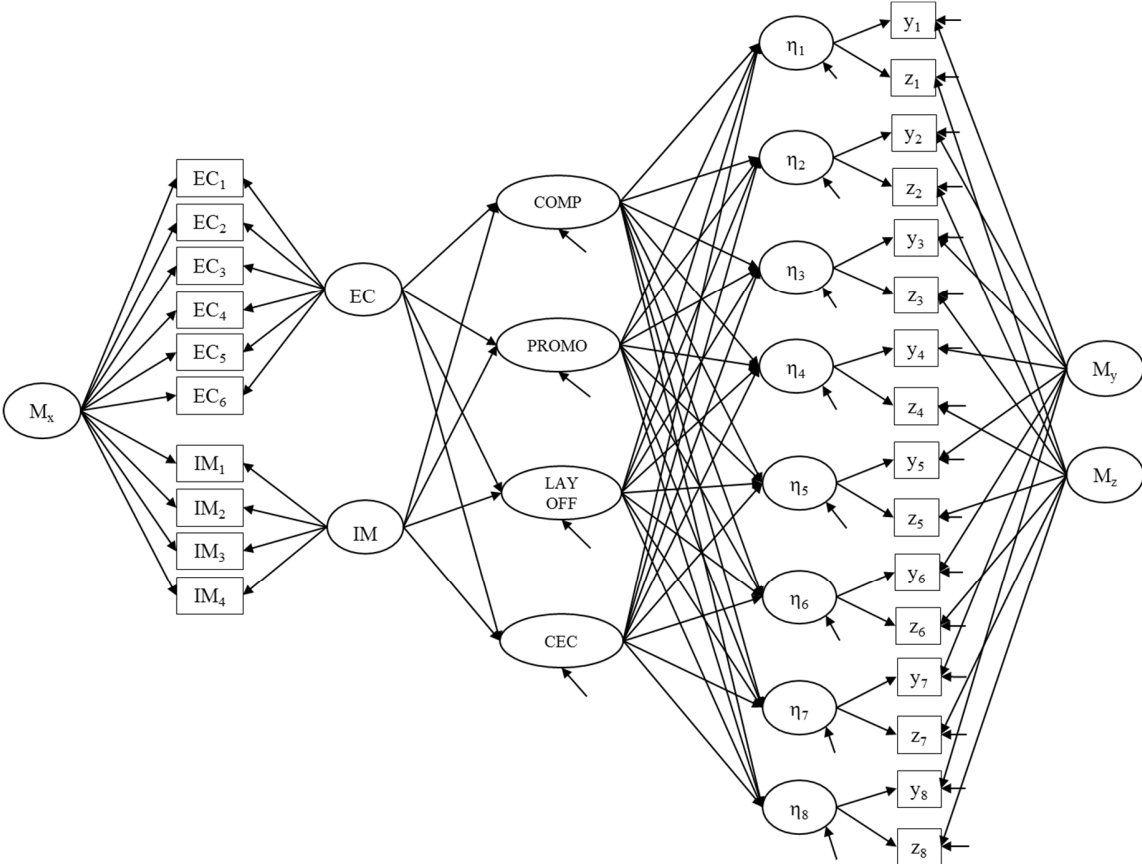   subsequent analyses in multi-group mode.
   b) Multi-indicator measurement:
      If multiple ratings for each profile have been collected, specify a second-order factor structure with method-specific i
      factors.
   c) Weight factor specification:
      • Specify the intercept and weight factors.
      • If some attributes have more than two levels, select an appropriate specification: If the levels are nominal, (q-
        weight factors are needed for q levels. If the levels are (assumed to be) ordinal or metric, the researcher may
        use a linear coding scheme (allocated coding) for simplicity, but it is necessary to test whether this assumptio
        appropriate (by evaluating global and local model fit).
   d) Residual variance specification: Test whether residual variance terms can be set to equality across the different profil
      by comparing a model without the equality constraint to a model with the equality constraint imposed and evaluating
      deterioration in fit (e.g., using a χ^2 difference test).
2. Model evaluation. Evaluate the core model:
   a) Evaluate global model fit (based on χ^2 and alternative fit indices such as CFI, TLI, RMSEA, SRMR).
   b) Check for local misfit (e.g., based on modification indices) to identify specific model constraints that may be problem
   c) Verify that parameter estimates are meaningful (e.g., no negative variance estimates).
   d) Verify that explained variance in the ratings (or rating factors in the case of multi-indicator models) is satisfactory (ty
      $R^2 > .50$).
3. Model adaptation. Add interaction effects if required:
   Test models with interaction terms and evaluate model fit relative to a model without the interaction terms if one or more of t
   following conditions hold: (a) the theoretical model requires interaction terms, (b) the explained variance in the ratings is
   unsatisfactory, (c) model fit in step 2 is unsatisfactory, and/or (d) indices of local misfit (esp. modification indices) suggest th
   for profiles that share the same combination of attribute levels are more strongly correlated than is implied by the model.
4. Model integration with other variables. Integrate the core SEMWISE model into a broader nomological network if applicable
   a) Interpret the variance estimates of the weight factors. For weight factors with a non-zero variance, go to step 4b. For
      factors with non-significant variance, set the variance to zero; step 4b does not apply for these weight factors.
   b) Add antecedents, correlates and outcome variables to the model.
   c) Multi-group comparison. In a multi-group setting, test for between-group invariance of the parameters of interest (es
      factor means, variance and covariance terms, and regression weights linking weight factors to other variables).
5. Model interpretation.
   Interpret the parameter estimates and report.

Figure 6. Suggested SEMWISE modeling steps.

Appendix A

Comparison of the SEMWISE and MLM analysis approaches

This appendix compares the SEMWISE and multi-level modeling (MLM) approaches in terms of data setup, data analysis, and (interpretation of) results as applied to the stylized example shown in Figure 1 of the main text. Figure A1 shows how the data file is structured in the MLM approach (left-hand panel) compared to the SEMWISE approach (right-hand panel), using the four responses of the fictitious respondent in Figure 1 in the main text as an example.

Multilevel data setup

Respondent	Profile	Profile warmth	Profile competence	Rating
1	1	1	-1	2
1	2	-1	1	4
1	3	1	1	5
1	4	-1	-1	1
2	1	...	...	...
2	2	...	...	...
...	...	...	...	...

SEMWISE data setup

Respondent	Rating for profile 1	Rating for profile 2	Rating for profile 3	Rating for profile 4
1	2	4	5	1
2	...	...	...	...
3	...	...	...	...

Figure A1. Data setup in a simplified policy capturing study.

As shown in Figure A1, in the MLM dataset, respondents' reactions to the four profiles (obtained by crossing the two levels of warmth with the two levels of competence) are specified on four separate lines of data (i.e., each line represents the rating of one profile, with multiple lines for each respondent). In addition, the profile attribute levels are represented by two additional variables, one containing the effect-coded attribute levels for warmth for each profile, the other containing the effect-coded attribute levels for competence for each profile. The profiles' attribute levels are repeated across respondents, but the ratings are respondent-specific. For the SEMWISE approach, each participant has one line of data and there are four columns of ratings corresponding to the ratings of the four profiles. In other words, MLM requires data in long format, SEMWISE requires data in wide format. In

the SEMWISE approach, the attribute levels of the profiles are not part of the dataset but are

specified as fixed model parameters in the analytical model (see the loadings in Figure 1).

In the MLM approach, the ratings of the teammate profiles are regressed on each

profile's warmth and competence level, where (for the sake of this example) effect coding is

used to represent the profiles (i.e., −1 represents a low level, +1 represents a high level of an

attribute). The estimated regression coefficients are the weights (or utilities) that respondents

attach to warmth and competence, which are inferred from the overall ratings of the profiles.

In other words, the overall rating of a profile is decomposed into the weights of the attribute

levels that characterize the profile. It can be shown that when using MLM, the estimated

regression coefficients, which are allowed to vary across respondents, are a compromise

between (or weighted combination of) two types of regressions, a pooled regression and

individual-level regressions (Gelman & Hill, 2007). In a pooled regression, it is assumed that

all respondents assign the same weights to warmth and competence when rating teammates,

so the regression coefficients are fixed to be equal across respondents. In an individual-level

regression, it is assumed that each respondent assigns idiosyncratic weights to warmth and

competence when rating teammates, so a separate regression equation is estimated for each

respondent across the rated profiles (four in the present case). If there is little variability in

coefficients across respondents, the MLM estimates will be close to the pooled estimates, but

as the variability in coefficients across respondents increases, the MLM estimates move

toward the individual-level estimates. The advantage of the MLM regression coefficients is

that, on the one hand, the limiting assumption of effect homogeneity is relaxed and that, on

the other hand, the estimates tend to be more stable than the individual-level regression

coefficients (which are often based on a relatively small number of distinct profiles).

In the SEMWISE approach, the estimated weights are the same as in the MLM

approach, but the way in which the model is specified and the weights are estimated is quite

different. Instead of regressing teammate ratings on warmth and competence, one specifies a

factor model in which the ratings of the four experimental profiles are treated as the observed

indicators of three latent factors: an intercept factor, a weight factor for warmth, and a weight

factor for competence. In order to estimate a factor model, the data have to be structured

differently, as shown in Figure A1.

Although the SEMWISE model is a factor model, it should be noted that the

SEMWISE factor model differs from a conventional factor model in that the factor loadings

are fixed to particular values (analogous to the effect-coded independent variables in the

MLM approach) and each indicator (i.e., each profile rating) loads on multiple factors, the

reason being that each profile rating is assumed to be a function of the conjoint effect of

multiple weight factors (e.g., the rating of the profile with high warmth and high competence

depends on the weight that respondents attach to warmth and the weight that respondents

attach to competence).

The weight factor scores in the SEMWISE approach are identical to the regression

coefficients estimated in the MLM approach. Specifically, the latent intercept factor captures

the average rating that each respondent gives to the entire set of profiles. The latent intercept

factor has unit loadings on the four indicators (the ratings of the four profiles) and

corresponds to the intercept term in the MLM approach. The four profile ratings have

loadings on the latent warmth and competence weight factors, and these loadings correspond

to the profiles' effect codes (for warmth and competence) in the MLM approach. Thus, both

approaches model each profile rating as a function of its effect-coded attribute levels and the

respective weights (regression coefficients in MLM, weight factor scores in SEMWISE) of

these attribute levels. Since the loadings are effect-coded as -1 for low and $+1$ for high

warmth and competence, respectively, twice the estimated factor score is the difference in the

weight attached to low and high warmth or competence.

Below we provide Mplus syntax to simulate data corresponding to the example shown

in Figure 1 and to analyze the data in an equivalent way using either SEMWISE or MLM

(see Figure A1). The Mplus output shows that the parameter estimates are the same across the

MLM and SEMWISE analyses, although the terminology differs across approaches.

```
5. Data generation

   TITLE: Data generation for SEMWISE vs. MLM (Fig 1 and Fig A1);
   MONTECARLO:
   NAMES = y1-y4;                    !response variables: profile rating;
   NOBS = 250;                       !sample size
   SAVE = example_wide.dat;          !generated data filename
   SEED =  0;                        !results can be replicated exactly
   MODEL POPULATION:                 !true model for data generation
   icept  BY y1-y4@1;                !intercept factor
   wfwarm BY y1@1 y2@-1 y3@1 y4@-1;  !weight factor for warmth
   wfcomp BY y1@-1 y2@1 y3@1 y4@-1;  !weight factor for competence
   icept*.7 wfwarm*.7 wfcomp*.7;     !factor variances are .7
   icept WITH wfwarm*.1;             !factor covariance
   icept WITH wfcomp*.1;             !factor covariance
   wfwarm WITH wfcomp*.1;            !factor covariance
   y1-y4*.2;                         !residual variance of response
   variable
   [y1-y4@0];                        ! intercepts of response variable
   [icept*3 wfwarm*.6 wfcomp*.3];    !intercept and weight factor means
   MODEL: y1-y4 with y1-y4;          !observed sample covariances

6. Data analysis using the SEMWISE approach

   TITLE: SEMWISE analysis for the example in Figures 1 and 2;
   DATA: FILE = example_wide.dat;    !use the data in wide format
   VARIABLE: NAMES = y1-y4;          !response variables
   MODEL:
   icept  by y1-y4@1;                !intercept factor
   wfwarm by y1@1 y2@-1 y3@1 y4@-1;  !weight factor for warmth
   wfcomp by y1@-1 y2@1 y3@1 y4@-1;  !weight factor for competence
   [y1-y4@0];                        !response intercepts are set to zero
   [icept wfwarm wfcomp];            !freely estimated factor means
   y1-y4(e);                         !residual variances equal for
   correspondence with MLM
   OUTPUT: TECH1 STANDARDIZED;        !standardized keyword gives R²

7. Data analysis using the MLM approach

   Title: Multilevel modeling (MLM) analysis for Figures 1 and 2;
   data: file = example_wide.dat;
   DATA WIDETOLONG:
      WIDE = y1-y4 | W1-W4 | C1-C4;
      LONG = y | xwarm | xcomp;
      IDVARIABLE = person;
      REPETITION = profile;
   VARIABLE: names = y1 y2 y3 y4;
             usevar = W1 W2 W3 W4 C1 C2 C3 C4 y xwarm xcomp person;
             AUXILIARY = W1 W2 W3 W4 C1 C2 C3 C4;
   cluster = person;
   within = xwarm xcomp;
   DEFINE:
     W1 =  1;
     W2 = -1;
     W3 =  1;
     W4 = -1;
     C1 = -1;
```

```
    C2 =  1;
    C3 =  1;
    C4 = -1;
  analysis: type =  random twolevel;
           estimator = ml;
  model:
  %within%
  wfwarm | y on xwarm;
  wfcomp | y on xcomp;
  %between%
  wfwarm wfcomp;
  y;
  wfwarm with y;
  wfcomp with y wfwarm;
```

8. Selected output for both approaches

SEMWISE						MLM				
	Est.	S.E.	t	p			Est.	S.E.	t	p
						Between Level				
WFWARM WITH						WFWARM WITH				
ICEPT	0.138	0.049	2.815	0.005		Y	0.138	0.049	2.819	0.005
WFCOMP WITH						WFCOMP WITH				
ICEPT	0.118	0.048	2.451	0.014		Y	0.118	0.046	2.565	0.010
WFWARM	0.136	0.049	2.788	0.005		WFWARM	0.136	0.054	2.497	0.013
Means						Means				
ICEPT	3.036	0.055	55.193	0.000		Y	3.036	0.055	55.192	0.000
WFWARM	0.545	0.055	9.855	0.000		WFWARM	0.545	0.055	9.854	0.000
WFCOMP	0.294	0.055	5.364	0.000		WFCOMP	0.294	0.055	5.363	0.000
Variances						Variances				
ICEPT	0.707	0.068	10.434	0.000		Y	0.707	0.066	10.661	0.000
WFWARM	0.715	0.069	10.442	0.000		WFWARM	0.715	0.065	10.992	0.000
WFCOMP	0.700	0.067	10.426	0.000		WFCOMP	0.700	0.069	10.185	0.000
Residual Variances						Within Level				
Y1	0.196	0.018	11.180	0.000						
Y2	0.196	0.018	11.180	0.000		Residual Variances				
Y3	0.196	0.018	11.180	0.000		Y	0.196	0.016	12.575	0.000
Y4	0.196	0.018	11.180	0.000						

Appendix B

Correlation matrix for empirical application 1

	1	2	3	4	5	6	7	8
1 Female								
2 HHL	.009							
3 HLL	.039	.481						
4 HHH	-.023	.420	.297					
5 HLH	-.062	.222	.376	.418				
6 LHL	.055	.547	.382	.358	.103			
7 LLL	.027	.432	.585	.280	.344	.415		
8 LHH	.043	.415	.337	.556	.337	.418	.289	
9 LLH	.045	.169	.398	.362	.595	.188	.459	.414

Note: Correlations based on data setup in wide format (responses to the experimental profiles correspond to variables 2 to 9). Female refers to respondent gender (0 = male, 1 = female). The other variable names refer to the levels (L = low, H = high) of the three attributes attractiveness, warmth and competence.

Appendix C

Correlation matrix of empirical application 2

	y1	y2	y3	y4	y5	y6	y7	y8	z1	z2	z3	z4	z5	z6	z7	z8	EC1	EC2	EC3	EC4	EC5	EC6	IM1	IM2	IM3	IM4	IM5	IM6	IM7	IM8	IM9
y2	.22																														
y3	.15	.22																													
y4	.27	.28	.23																												
y5	-.08	.22	.16	.16																											
y6	.13	.09	.12	.17	.13																										
y7	.15	.14	-.07	.17	.24	.37																									
y8	.18	.25	.08	-.07	.18	.10	.22																								
z1	.67	.30	.19	.26	.04	.12	.16	.24																							
z2	.25	.74	.25	.25	.25	.13	.14	.22	.50																						
z3	.14	.27	.69	.22	.16	.13	-.03	.09	.38	.44																					
z4	.23	.28	.22	.75	.21	.19	.15	.01	.40	.44	.38																				
z5	-.04	.17	.14	.15	.77	.17	.20	.14	.15	.37	.29	.37																			
z6	.17	.14	.19	.21	.14	.75	.31	.13	.34	.33	.40	.35	.30																		
z7	.18	.17	-.07	.17	.26	.40	.79	.24	.32	.32	.08	.30	.37	.46																	
z8	.19	.24	.13	.02	.26	.14	.24	.70	.45	.37	.30	.22	.36	.36	.40																
EC1	-.19	.05	.15	.06	.15	-.10	-.23	-.08	-.15	.04	.09	.07	.11	-.12	-.19	-.08															
EC2	-.13	.03	.18	.06	.08	-.16	-.28	-.13	-.11	.03	.09	.07	.07	-.15	-.29	-.11	.60														
EC3	-.17	.07	.13	.02	.15	-.14	-.26	-.13	-.16	.06	.06	.06	.14	-.15	-.26	-.11	.46	.48													
EC4	.03	-.15	-.18	-.18	-.18	.12	.24	.13	.04	-.11	-.10	-.16	-.15	.11	.23	.14	-.45	-.48	-.39												
EC5	.08	-.09	-.10	-.11	-.11	.09	.25	.11	.00	-.14	-.11	-.18	-.13	.08	.22	.09	-.36	-.37	-.28	.39											
EC6	.11	-.18	-.21	-.12	-.14	.18	.31	.12	.09	-.14	-.14	-.12	-.15	.14	.29	.09	-.47	-.57	-.51	.56	.46										
IM1	-.05	.04	.03	.03	.10	-.08	.02	-.03	-.09	-.04	-.03	-.03	.07	-.09	-.02	-.06	.07	.07	.12	.05	.04	-.03									
IM2	-.02	-.10	-.08	-.08	.06	.03	-.02	.01	.05	-.02	-.04	-.06	.03	.02	.07	.03	.02	-.04	-.03	-.01	-.05	.10	-.25								
IM3	-.06	.07	.08	.04	.07	.02	-.06	.01	.01	.07	.00	.03	.07	-.03	.00	.06	.16	.11	.11	-.10	-.03	-.12	-.08	.19							
IM4	.04	.02	-.02	.10	-.05	.03	-.01	-.08	.05	.02	-.07	.07	-.04	-.01	.00	.00	.00	-.09	-.01	.06	.10	.11	.15	.04	.03						
IM5	.01	-.02	.03	.05	-.04	-.04	-.01	-.06	-.04	.01	.00	.06	-.04	-.04	.03	-.03	.09	.11	.20	-.10	.03	-.07	.01	.10	.12	-.02					
IM6	.01	.03	.04	-.01	-.07	.03	.03	.03	-.03	-.03	-.03	.04	-.03	-.03	.03	.00	-.02	.07	.07	-.06	.09	-.04	.05	-.06	-.09	.07	.02				
IM7	-.05	-.07	.06	.02	-.03	.04	-.04	-.04	-.08	-.06	.06	.00	.04	.05	-.02	-.08	.04	.09	.10	.04	.04	-.06	.27	-.18	-.17	.02	.04	.13			
IM8	.02	.05	-.03	-.01	.08	-.07	.11	.09	.03	.03	-.02	-.01	.10	-.07	.09	.06	-.10	-.15	-.02	.15	.09	.17	.25	-.09	-.11	.16	.00	.04	.09		
IM9	-.03	.01	-.07	-.09	.00	-.05	.00	.06	-.01	.06	-.09	.00	.01	-.05	.04	.11	.07	.00	.12	-.01	-.07	-.03	-.13	.24	.36	-.01	.17	-.11	-.36	-.08	
IM10	-.05	-.10	.06	.00	.03	.00	-.09	-.11	-.04	-.03	.04	.04	.03	.02	-.09	-.09	.17	.22	.14	-.11	-.18	-.12	-.10	.23	.21	-.22	.27	-.04	-.02	-.01	.20

Note: Correlations based on data setup in wide format. Variables y1-y8 refer to profile ratings using the first item ('To what extent would you like to work for this company?' rated by manipulating a sliding bar linked to a smiley face with five levels ranging from 1= low to 5=high), z1-z8 to profile ratings using the second item ('How attractive do you find this company?' rated by means of a continuous sliding scale marked by five stars with scores ranging from zero to five). EC1-EC6 refer to the Environmental Concern scale items, IM1-IM10 to the Impression Management scale items.

Appendix D

Mplus, R, and LISREL syntax for analyzing the data of the SEMWISE core model and several extensions

This web appendix provides Mplus syntax for generating artificial data and Mplus, R, and LISREL syntax for analyzing the data of the

SEMWISE core model and several extensions.

Mplus data generation	Mplus data analysis	R data analysis	LISREL data analysis

!Example 1 data generation;
Title: SEMWISE core model data generation (see Figure 2);
montecarlo:
names = y1-y8;
nobs = 500;
save = semwise_core.dat;
model population:
eta0 by y1-y8@1;
eta1 by y1@1 y2@1 y3@1 y4@1 y5@-1 y6@-1 y7@-1 y8@-1;
eta2 by y1@-1 y2@-1 y3@1 y4@1 y5@-1 y6@-1 y7@1 y8@1;
eta3 by y1@1 y2@-1 y3@1 y4@-1 y5@1 y6@-1 y7@1 y8@-1;
eta0-eta3*.7;
eta0 with eta1*.1;
eta0 with eta2*.1;
eta0 with eta3*.1;
eta1 with eta2*.1;
eta1 with eta3*.1;
eta2 with eta3*.1;
y1-y8*.2;
	!Example 1 data analysis;
	Title: SEMWISE core model data analysis (see Figure 2);
	data: file = semwise_core.dat;
	variable: names = y1-y8;
	model:
	eta0 by y1-y8@1;
	eta1 by y1@1 y2@1 y3@1 y4@1 y5@-1 y6@-1 y7@-1 y8@-1;
	eta2 by y1@-1 y2@-1 y3@1 y4@1 y5@-1 y6@-1 y7@1 y8@1;
	eta3 by y1@1 y2@-1 y3@1 y4@-1 y5@1 y6@-1 y7@1 y8@-1;
	eta0-eta3*.7;
	eta0 with eta1*.1;
	eta0 with eta2*.1;
	eta0 with eta3*.1;
	eta1 with eta2*.1;
	eta1 with eta3*.1;
	eta2 with eta3*.1;
	y1-y8*.5;
	[y1-y8@0]; [eta0-eta3];
		#Example 1 data analysis;
		#SEMWISE core model data analysis
		#(see Figure 2);
		library(lavaan)
		semwise_core <-
		read.table("semwise_core.dat")
		names(semwise_core)<-
		c("y1","y2","y3","y4","y5","y6","y7","y8")
		model <- '
		eta0=~1*y1+1*y2+1*y3+1*y4+1*y5+1*y6+1*y7+1*y8
		eta1=~1*y1+1*y2+1*y3+1*y4+-1*y5+-1*y6+-1*y7+-1*y8
		eta2=~-1*y1+-1*y2+1*y3+1*y4+-1*y5+-1*y6+1*y7+1*y8
		eta3=~1*y1+-1*y2+1*y3+-1*y4+1*y5+-1*y6+1*y7+-1*y8
		y1 ~0*1
		y2 ~0*1
		y3 ~0*1
		y4 ~0*1
		y5 ~0*1
		y6 ~0*1
		y7 ~0*1
		y8 ~0*1
		eta0~1
		eta1~1
			!Example 1 data analysis;
			SEMWISE core model data analysis (see Figure 2)
			DA NI=8 NO=0
			LA
			y1 y2 y3 y4 y5 y6 y7 y8
			RA FI= semwise_core.dat
			MO NY=8 NE=4 LY=FI TE=DI,FR AL=FR
			PS=SY,FR BE=ZE TY=ZE
			MA LY
			1 1 -1 1
			1 1 -1 -1
			1 1 1 1
			1 1 1 -1
			1 -1 -1 1
			1 -1 -1 -1
			1 -1 1 1
			1 -1 1 -1
			LE
			eta0 eta1 eta2 eta3
			OU MI SC

		eta2~1 eta3~1 ' fit <- sem(model, data=semwise_core, meanstructure = TRUE) summary(fit)	

!Example 2 data generation;
Title: Data generation with attributes: Three brands offered at three (non-linear) price levels;
montecarlo:
names = y1-y9;
nobs = 500;
save = semwise_nonbinary.dat;
model population:
brand2 by y1@-1 y2@-1 y3@-1 y4@1 y5@1 y6@1 y7@0 y8@0 y9@0;
brand3 by y1@-1 y2@-1 y3@-1 y4@0 y5@0 y6@0 y7@1 y8@1 y9@1;
price by y1@-1 y2*0.2 y3@1 y4@-1 y5*0.2 y6@1 y7@-1 y8*0.2 y9@1;
brand2-brand3*.9 price*.9;
brand2 with brand3*0.1;
brand2 with price*-.1;
brand3 with price*.1;
y1-y9*.2;
	!Example 2 data analysis;
	Title: nonbinary SEMWISE analysis;
	variable: names = y1-y9;
	data: file = semwise_nonbinary.dat;
	model:
	brand2 by y1@-0.5 y2@-0.5 y3@-0.5 y4@1 y5@1 y6@1 y7@0 y8@0 y9@0 ;
	brand3 by y1@-0.5 y2@-0.5 y3@-0.5 y4@0 y5@0 y6@0 y7@1 y8@1 y9@1 ;
	price by y1@-1 y2*0.2 y3@1 y4@-1 y5*0.2 y6@1 y7@-1 y8*0.2 y9@1 ;
	price by y2 y5 y8 (b);
	[y1-y9@0];
	[brand2 brand3 price];
		#Example 2 data analysis;
		#nonbinary SEMWISE analysis;
		semwise_nonbinary <-
		read.table("semwise_nonbinary.dat")
		names(semwise_nonbinary)<-
		  c("y1","y2","y3","y4","y5","y6","y7","y8", "y9")
		model <- '
		brand2 =~ -.5*y1 + -.5*y2 + -.5*y3 + 1*y4 + 1*y5 + 1*y6 + 0*y7 + 0*y8 + 0*y9
		brand3 =~ -.5*y1 + -.5*y2 + -.5*y3 + 0*y4 + 0*y5 + 0*y6 + 1*y7 + 1*y8 + 1*y9
		price =~ -1*y1 + b*y2 + 1*y3 + -1*y4 + b*y5 + 1*y6 + -1*y7 + b*y8 + 1*y9
		y1 ~0*1
		y2 ~0*1
		y3 ~0*1
		y4 ~0*1
		y5 ~0*1
		y6 ~0*1
		y7 ~0*1
		y8 ~0*1
		y9 ~0*1
		brand2~1
		brand3~1
		price~1
		'
		
		fit <- sem(model, data=semwise_nonbinary,
		meanstructure = TRUE)
		summary(fit)
			!Example 2 data analysis;
			Nonbinary SEMWISE analysis
			DA NI=9 NO=0
			LA
			y1 y2 y3 y4 y5 y6 y7 y8 y9
			RA FI= semwise_nonbinary.dat
			MO NY=9 NE=3 LY=FR TE=DI,FR AL=FR
			PS=SY,FR BE=ZE TY=ZE
			PA LY
			0 0 0
			0 0 2
			0 0 0
			0 0 0
			0 0 2
			0 0 0
			0 0 0
			0 0 2
			0 0 0
			MA LY
			-0.5 -0.5 -1.0
			-0.5 -0.5 0.0
			-0.5 -0.5 1.0
			 1.0 0.0 -1.0
			 1.0 0.0 0.0
			 1.0 0.0 1.0
			 0.0 1.0 -1.0
			 0.0 1.0 0.0
			 0.0 1.0 1.0
			LE
			brand2 brand3 price
			OU MI SC

!Example 3 data generation;	!Example 3 data analysis;	#Example 3 data analysis; #Two methods SEMWISE analysis;	!Example 3 data analysis;

Title: Two methods SEMWISE data generation (Figure 3);
montecarlo:
names = y1-y8 z1-z8;
nobs = 500;
save = semwise2methods.dat;
model population:
My by y1-y8@1;
Mz by z1-z8@1;
eta1 by y1@1 z1@1.2;
eta2 by y2@1 z2@1.2;
eta3 by y3@1 z3@1.2;
eta4 by y4@1 z4@1.2;
eta5 by y5@1 z5@1.2;
eta6 by y6@1 z6@1.2;
eta7 by y7@1 z7@1.2;
eta8 by y8@1 z8@1.2;
ksi1 by eta1@-1 eta2@-1 eta3@-1 eta4@-1
eta5@1 eta6@1 eta7@1 eta8@1;
ksi2 by eta1@-1 eta2@-1 eta3@1 eta4@1
eta5@-1 eta6@-1 eta7@1 eta8@1;
ksi3 by eta1@-1 eta2@1 eta3@1 eta4@1
eta5@1 eta6@1 eta7@-1 eta8@-1;
ksi4 by eta1@-1 eta2@1 eta3@-1 eta4@1
eta5@-1 eta6@1 eta7@-1 eta8@1;
ksi1-ksi4*.8;
ksi1 with ksi2*.1 ksi3*.1 ksi4*.1;
ksi2 with ksi3*.1 ksi4*.1;
ksi3 with ksi4*.1;
y1-y8*.2;
z1-z8*.3;
My*.2 Mz*.2;
My with Mz*.1;
My Mz with ksi1-ksi4@0;
eta1-eta8*.2;
[z1-z8@0];
[eta1-eta8@0];
[My*0 Mz*0];
[ksi1*.5 ksi2*.5 ksi3*-.25 ksi4*.25];
	Title: Two methods SEMWISE data analysis (Figure 3);
	data: file = semwise2methods.dat;
	variable: names = y1-y8 z1-z8;
	model:
	My by y1-y8@1;
	Mz by z1-z8@1;
	eta1 by y1@1
	   z1(b);
	eta2 by y2@1
	   z2(b);
	eta3 by y3@1
	   z3(b);
	eta4 by y4@1
	   z4(b);
	eta5 by y5@1
	   z5(b);
	eta6 by y6@1
	   z6(b);
	eta7 by y7@1
	   z7(b);
	eta8 by y8@1
	   z8(b);
	KSI1 by eta1@-1 eta2@-1 eta3@-1 eta4@-1
	eta5@1 eta6@1 eta7@1 eta8@1;
	KSI2 by eta1@-1 eta2@-1 eta3@1 eta4@1
	eta5@-1 eta6@-1 eta7@1 eta8@1;
	KSI3 by eta1@-1 eta2@1 eta3@1 eta4@1
	eta5@1 eta6@1 eta7@-1 eta8@-1;
	KSI4 by eta1@-1 eta2@1 eta3@-1 eta4@1
	eta5@-1 eta6@1 eta7@-1 eta8@1;
	My with ksi1-ksi4@0;
	Mz with ksi1-ksi4@0;
	[y1-y8@0];
	[z1-z8@0];
	[eta1-eta8@0];
	[My*0 Mz*0];
	[ksi1*.5 ksi2*.5 ksi3*-.25 ksi4*.25];
		semwise2methods <-
		read.table("semwise2methods.dat")
		names(semwise2methods)<-
		  c("y1","y2","y3","y4","y5","y6","y7","y8",
		"z1","z2","z3","z4","z5","z6","z7","z8")
		
		model <-
		'My=~1*y1+1*y2+1*y3+1*y4+1*y5+1*y6+1*y7+
		1*y8
		Mz=~1*z1+1*z2+1*z3+1*z4+1*z5+1*z6+1*z7+1
		*z8
		eta1 =~ 1*y1 + b*z1
		eta2 =~ 1*y2 + b*z2
		eta3 =~ 1*y3 + b*z3
		eta4 =~ 1*y4 + b*z4
		eta5 =~ 1*y5 + b*z5
		eta6 =~ 1*y6 + b*z6
		eta7 =~ 1*y7 + b*z7
		eta8 =~ 1*y8 + b*z8
		ksi1=~-1*eta1+-1*eta2+-1*eta3+-
		1*eta4+1*eta5+1*eta6+1*eta7+1*eta8
		ksi2=~-1*eta1+-1*eta2+1*eta3+1*eta4+-
		1*eta5+-1*eta6+1*eta7+1*eta8
		ksi3=~-1*eta1+-
		1*eta2+1*eta3+1*eta4+1*eta5+1*eta6+-
		1*eta7+-1*eta8
		ksi4=~-1*eta1+1*eta2+-1*eta3+1*eta4+-
		1*eta5+1*eta6+-1*eta7+1*eta8
		My ~~ 0*ksi1
		My ~~ 0*ksi2
		My ~~ 0*ksi3
		My ~~ 0*ksi4
		Mz ~~ 0*ksi1
		Mz ~~ 0*ksi2
		Mz ~~ 0*ksi3
		Mz ~~ 0*ksi4
		y1 ~0*1
		y2 ~0*1
		y3 ~0*1
			Two methods SEMWISE data analysis (Figure 3)
			DA NI=16 NO=0
			LA
			y1 y2 y3 y4 y5 y6 y7 y8 z1 z2 z3 z4 z5 z6 z7 z8
			RA FI = semwise2methods.dat
			MO NY=16 NE=10 NK=4 LY=FI TE=DI,FR
			AL=FI KA=FR PS=SY,FR GA=FI BE=ZE
			TY=ZE
			FR AL 9 AL 10
			FR LY 9 1 LY 10 2 LY 11 3 LY 12 4 LY 13 5 LY
			14 6 LY 15 7 LY 16 8
			EQ LY 9 1 LY 10 2 LY 11 3 LY 12 4 LY 13 5 LY
			14 6 LY 15 7 LY 16 8
			MA LY
			1 0 0 0 0 0 0 0 1 0
			0 1 0 0 0 0 0 0 1 0
			0 0 1 0 0 0 0 0 1 0
			0 0 0 1 0 0 0 0 1 0
			0 0 0 0 1 0 0 0 1 0
			0 0 0 0 0 1 0 0 1 0
			0 0 0 0 0 0 1 0 1 0
			0 0 0 0 0 0 0 1 1 0
			1 0 0 0 0 0 0 0 0 1
			0 1 0 0 0 0 0 0 0 1
			0 0 1 0 0 0 0 0 0 1
			0 0 0 1 0 0 0 0 0 1
			0 0 0 0 1 0 0 0 0 1
			0 0 0 0 0 1 0 0 0 1
			0 0 0 0 0 0 1 0 0 1
			0 0 0 0 0 0 0 1 0 1
			MA GA
			-1 -1 -1 -1
			-1 -1 -1 1
			-1 1 1 -1
			-1 1 1 1
			1 -1 1 -1
			1 -1 1 1
			1 1 -1 -1
			1 1 -1 1

		y4 ~0*1	0 0 0 0
		y5 ~0*1	0 0 0 0
		y6 ~0*1	PA PS
		y7 ~0*1	1
		y8 ~0*1	0 1
		z1 ~0*1	0 0 1
		z2 ~0*1	0 0 0 1
		z3 ~0*1	0 0 0 0 1
		z4 ~0*1	0 0 0 0 0 1
		z5 ~0*1	0 0 0 0 0 0 1
		z6 ~0*1	0 0 0 0 0 0 0 1
		z7 ~0*1	0 0 0 0 0 0 0 0 1
		z8 ~0*1	0 0 0 0 0 0 0 0 1 1
		eta1 ~0*1	LE
		eta2 ~0*1	eta1 eta2 eta3 eta4 eta5 eta6 eta7 eta8 My Mz
		eta3 ~0*1	LK
		eta4 ~0*1	ksi1 ksi2 ksi3 ksi4
		eta5 ~0*1	OU MI SC
		eta6 ~0*1	
		eta7 ~0*1	
		eta8 ~0*1	
		My~1	
		Mz~1	
		ksi1~1	
		ksi2~1	
		ksi3~1	
		ksi4~1	
		'	
		fit <- sem(model, data=semwise2methods, meanstructure = TRUE) summary(fit)	
!Example 4 data generation; Title: Two-group SEMWISE mimic (see Figure 4); montecarlo: names = y1-y8; ngroups = 2; nobs = 250 250; save = semwise2g.dat; model population:	!Example 4a data analysis; Title: SEMWISE analysis using binary covariate (Figure 4a); data: file = semwise2g.dat; variable: names = y1-y8 g; define: g = g-1; model: eta0 by y1-y8@1;	#Example 4a data analysis; #SEMWISE analysis using binary covariate (Figure 4a) semwise2g <- read.table("semwise2g.dat") names(semwise2g)<- c("y1","y2","y3","y4","y5","y6","y7","y8", "g") semwise2g[,9] <- semwise2g[,9]-1 model <- '	!Example 4a data analysis; SEMWISE analysis using binary covariate (Figure 4a) DA NI=9 NO=0 LA y1 y2 y3 y4 y5 y6 y7 y8 g RA FI= semwise2g.dat MO NY=8 NX=1 NE=4 LY=FI TE=DI,FR KA=FR AL=FR PS=SY,FR BE=ZE TY=ZE FI

eta0 by y1-y8@1;
eta1 by y1@1 y2@1 y3@1 y4@1 y5@-1
y6@-1 y7@-1 y8@-1;
eta2 by y1@-1 y2@-1 y3@1 y4@1 y5@-1
y6@-1 y7@1 y8@1;
eta3 by y1@1 y2@-1 y3@1 y4@-1 y5@1
y6@-1 y7@1 y8@-1;
eta0-eta3*.7;
eta0 with eta1*.1;
eta0 with eta2*.1;
eta0 with eta3*.1;
eta1 with eta2*.1;
eta1 with eta3*.1;
eta2 with eta3*.1;
y1-y8*.2;
model population-g2:
eta0*1;
[eta0*.5];
eta1-eta3*.25;
[eta1*-.25 eta2*-.5];
y1-y8*.8;
	eta1 by y1@1 y2@1 y3@1 y4@1 y5@-1 y6@-1 y7@-1 y8@-1;
	eta2 by y1@-1 y2@-1 y3@1 y4@1 y5@-1 y6@-1 y7@1 y8@1;
	eta3 by y1@1 y2@-1 y3@1 y4@1 y5@1 y6@-1 y7@1 y8@-1;
	eta0-eta3*.7;
	eta0 with eta1*.1;
	eta0 with eta2*.1;
	eta0 with eta3*.1;
	eta1 with eta2*.1;
	eta1 with eta3*.1;
	eta2 with eta3*.1;
	y1-y8*.5;
	eta0-eta3 on g;
	[y1-y8@0];
	[eta0-eta3];
	
	!Example 4b data analysis;
	Title: Two-group SEMWISE (Figure 4c);
	data: file = semwise2g.dat;
	variable:
	names = y1-y8 g;
	grouping = g (1 = male 2 = female);
	model:
	eta0 by y1-y8@1;
	eta1 by y1@1 y2@1 y3@1 y4@1 y5@-1 y6@-1 y7@-1 y8@-1;
	eta2 by y1@-1 y2@-1 y3@1 y4@1 y5@-1 y6@-1 y7@1 y8@1;
	eta3 by y1@1 y2@-1 y3@1 y4@1 y5@1 y6@-1 y7@1 y8@-1;
	eta0-eta3*.7;
	eta0 with eta1*.1;
	eta0 with eta2*.1;
	eta0 with eta3*.1;
	eta1 with eta2*.1;
	eta1 with eta3*.1;
	eta2 with eta3*.1;
	y1-y8*.5;
		eta0=~1*y1+1*y2+1*y3+1*y4+1*y5+1*y6+1*y7+1*y8
		eta1=~1*y1+1*y2+1*y3+1*y4+-1*y5+-1*y6+-1*y7+-1*y8
		eta2=~-1*y1+-1*y2+1*y3+1*y4+-1*y5+-1*y6+1*y7+1*y8
		eta3=~1*y1+-1*y2+1*y3+-1*y4+1*y5+-1*y6+1*y7+-1*y8
		eta0 ~ g
		eta1 ~ g
		eta2 ~ g
		eta3 ~ g
		y1 ~0*1
		y2 ~0*1
		y3 ~0*1
		y4 ~0*1
		y5 ~0*1
		y6 ~0*1
		y7 ~0*1
		y8 ~0*1
		eta0~1
		eta1~1
		eta2~1
		eta3~1
		'
		fit <- sem(model, data=semwise2g,
		meanstructure = TRUE)
		summary(fit)
		
		#Example 4b data analysis;
		#SEMWISE analysis using binary covariate (Figure 4c)
		semwise2g <- read.table("semwise2g.dat")
		names(semwise2g)<-
		c("y1","y2","y3","y4","y5","y6","y7","y8", "g")
		model <- '
		eta0=~1*y1+1*y2+1*y3+1*y4+1*y5+1*y6+1*y7+1*y8
		eta1=~1*y1+1*y2+1*y3+1*y4+-1*y5+-1*y6+-1*y7+-1*y8
			MA LY
			1 1 -1 1
			1 1 -1 -1
			1 1 1 1
			1 1 1 -1
			1 -1 -1 1
			1 -1 -1 -1
			1 -1 1 1
			1 -1 1 -1
			FR GA 1 1 GA 2 1 GA 3 1 GA 4 1
			LE
			eta0 eta1 eta2 eta3
			OU MI SC
			
			!Example 4b data analysis;
			Two-group SEMWISE (Figure 4c) - Males
			DA NI=9 NO=250 NG=2
			LA
			y1 y2 y3 y4 y5 y6 y7 y8 g
			RA FI=semwise2g-m.dat
			SE
			1 2 3 4 5 6 7 8/
			MO NY=8 NE=4 LY=FI TE=DI,FR AL=FR
			PS=SY,FR BE=ZE TY=ZE
			MA LY
			1 1 -1 1
			1 1 -1 -1
			1 1 1 1
			1 1 1 -1
			1 -1 -1 1
			1 -1 -1 -1
			1 -1 1 1
			1 -1 1 -1
			LE
			eta0 eta1 eta2 eta3
			OU MI SC
			
			Two-group SEMWISE (Figure 4c) - Females
			DA NI=9 NO=250
			LA

	`[y1-y8@0];`
	`model male:[eta0-eta3];`
	`model female:[eta0-eta3];`
		`eta2=~-1*y1+-1*y2+1*y3+1*y4+-1*y5+-`
		`1*y6+1*y7+1*y8`
		`eta3=~1*y1+-1*y2+1*y3+-1*y4+1*y5+-`
		`1*y6+1*y7+-1*y8`
		`y1        ~0*1`
		`y2        ~0*1`
		`y3        ~0*1`
		`y4        ~0*1`
		`y5        ~0*1`
		`y6        ~0*1`
		`y7        ~0*1`
		`y8        ~0*1`
		`eta0~1`
		`eta1~1`
		`eta2~1`
		`eta3~1`
		`'`
		`fit <- sem(model, data=semwise2g,`
		`meanstructure = TRUE, group = "g")`
		`summary(fit)`
			`y1 y2 y3 y4 y5 y6 y7 y8 g`
			`RA FI=semwise2g-f.dat`
			`SE`
			`1 2 3 4 5 6 7 8/`
			`MO NY=8 NE=4 LY=FI TE=DI,FR AL=FR`
			`PS=SY,FR BE=ZE TY=ZE`
			`MA LY`
			`1 1 -1 1`
			`1 1 -1 -1`
			`1 1 1 1`
			`1 1 1 -1`
			`1 -1 -1 1`
			`1 -1 -1 -1`
			`1 -1 1 1`
			`1 -1 1 -1`
			`LE`
			`eta0 eta1 eta2 eta3`
			`OU MI SC`

`!Example 5 data generation;`
`Title: SEMWISE with outcome data`
`generation (Figure 4a and 4b);`
`montecarlo:`
`names = outcome y1-y4 x;`
`nobs = 500;`
`nreps = 1;`
`save = semwise_mediation.dat;`
`model population:`
`model population:`
`eta0 by y1-y4@1;`
`eta1 by y1@1 y2@-1 y3@1 y4@-1;`
`eta2 by y1@1 y2@1 y3@-1 y4@-1;`
`y1-y4*.2;`
`eta0*1 eta1*.96 eta2*.84;`
`eta0-eta2 with eta0-eta2*0;`
`outcome on eta0*0 eta1*.6 eta2*-.4;`
`outcome*.5;`
`eta0 on x*0;`
`eta1 on x*.2;`
	`!Example 5 data analysis;`
	`Title: SEMWISE with outcome data analysis`
	`(Figure 4a and 4b);`
	`data: file = semwise_mediation.dat;`
	`variable: names = outcome y1-y4 x;`
	`model:`
	`eta0 by y1-y4@1;`
	`eta1 by y1@1 y2@-1 y3@1 y4@-1;`
	`eta2 by y1@1 y2@1 y3@-1 y4@-1;`
	`outcome on eta0-eta2;`
	`[y1-y4@0]; [eta0-eta2]; [x];`
	`eta0-eta2 with eta0-eta2*0;`
	`eta0-eta2 on x;`
		`#Example 5 data analysis;`
		`#SEMWISE with outcome data analysis (Figure`
		`4a and 4b)`
		`semwise_mediation <-`
		`read.table("semwise_mediation.dat")`
		`names(semwise_mediation)<-`
		`c("outcome", "y1","y2","y3","y4", "x")`
		`model <- '`
		`eta1=~1*y1+1*y2+1*y3+1*y4`
		`eta2=~1*y1+-1*y2+1*y3+-1*y4`
		`eta3=~1*y1+1*y2+-1*y3+-1*y4`
		`outcome ~ eta1 + eta2 + eta3`
		`eta1 ~ x`
		`eta2 ~ x`
		`eta3 ~ x`
		`y1~0*1`
		`y2~0*1`
		`y3~0*1`
		`y4~0*1`
		`eta1~1`
			`!Example 5 data analysis;`
			`SEMWISE with outcome data analysis (Figure`
			`4a and 4b)`
			`DA NI=6 NO=0`
			`LA`
			`outcome y1 y2 y3 y4 x`
			`RA FI= semwise_mediation.dat`
			`SE`
			`2 3 4 5 1 6/`
			`MO NY=5 NX=1 NE=4 LY=FI TE=DI,FR`
			`KA=FR AL=FR GA=FR TY=ZE PS=SY BE=FI`
			`FI`
			`MA LY`
			`1 1 1 0`
			`1 -1 1 0`
			`1 1 -1 0`
			`1 -1 -1 0`
			`0 0 0 1`
			`FI GA 4 1`
			`FR BE 4 1 BE 4 2 BE 4 3`

eta2 on x*.4; [x*0]; x*1;		eta2~1 eta3~1 eta2 ~~ eta1 eta3 ~~ eta1 eta3 ~~ eta2 ' fit <- sem(model, data=semwise_mediation, meanstructure = TRUE) summary(fit)	PA PS 1 1 1 1 1 1 0 0 0 1 FI TE 5 5 LE eta0 eta1 eta2 outcome OU MI SC