

Advanced multilevel modeling for a science of groups:  
A short primer on multilevel structural equation modeling

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In Press: Group Dynamics: Theory, Research, and Practice

Acknowledgments: The preparation of the manuscript was supported by a Deutsche Forschungsgemeinschaft research fellowship to Oliver Christ (CH 743, 2-1), a Leverhulme Trust Programme Grant to Miles Hewstone and Katharina Schmid, and a Swiss National Science Foundation to Eva G. T. Green (grant nr. 10FI13\_133957/1).

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## Abstract

A science of groups needs to take different levels of analysis into account since only multilevel perspectives provide a full and realistic picture of processes within and between social groups. A multilevel perspective, however, requires appropriate statistical models. Conventional multilevel regression models suffer from a number of limitations. Amongst these are the restriction to include only manifest variables and only one level 1 outcome variable. Moreover, it is not possible to test complex models (i.e., with multiple mediators and outcomes in a single step). In this paper, we introduce multilevel structural equation modeling (MSEM) as a new and promising development within psychological methods that helps overcome the limitations inherent in conventional MLM. MSEM combines SEM with MLM and offers the best of both worlds. Because MSEM allows using latent instead of manifest variables, measurement error can be taken into account. Moreover, the measurement model can be tested on both the within and between-levels of analysis. MSEM enables researchers to specify level 2 outcome variables and allows the researcher to test complex multilevel models (i.e., simultaneous tests of multiple direct and indirect effects). We illustrate the potential of MSEM using three examples from our own research, provide the corresponding software code as online supplementary material, and discuss important practical issues.

**Keywords:** Multilevel analysis; multilevel structural equation modeling; psychology of groups; levels of analysis; intergroup contact

Word count: 210

## Advanced multilevel modeling for a science of groups:

### A short primer on multilevel structural equation modeling

Social groups exist whenever two or more individuals define themselves as members of a group (Tajfel, 1981). In the terminology of multilevel modeling, individuals are nested within different social groups. Moreover, groups and individuals are not detached from the broader social context (such as nations, regions, districts, neighborhoods) in which they are located (Pettigrew, 2006). Thus, individuals and social groups are nested within different social contexts. This is not a new observation; the importance of different levels of analysis has been acknowledged within psychology for a long time (e.g., Doise, 1980; Pettigrew, 1996).

A comprehensive “science of groups” benefits from empirically examining these different levels of analysis simultaneously (Moritz & Watson, 1998). In the present paper, we introduce multilevel structural equation modeling as a relatively new statistical development that helps to deal with such “multilevel” data. Compared to conventional multilevel regression models, multilevel structural equation modeling (MSEM) offers a number of advantages: it combines multilevel modeling (MLM; e.g., simultaneous analysis of data from different levels of analysis) and structural equation modeling (SEM; e.g., latent variable analysis). A central aim of the current paper is to provide a primer on the use of MSEM. We therefore do not provide a detailed technical introduction into MSEM, but rather illustrate the potential of MSEM for a science of groups using three examples from our own research.

In Example 1 (Christ et al., 2014), we were interested in the contextual effect of positive intergroup contact. Using a number of cross-sectional and longitudinal survey data sets, we compared the individual-level effect of intergroup contact on outgroup attitudes with the social context level (e.g., districts, neighborhoods) effect of intergroup contact. A contextual effect is the difference between the effects on different levels of analysis. As we

will show below, testing a contextual effect with MSEM is superior to a test with conventional MLM.

In the second example (Green, Sarrasin, Baur, & Fasel, 2016), we examined the association between the presence of immigrant groups that are often targeted by radical right-wing parties and citizens' electoral support for these parties on the district level. As a level 2 outcome variable, we used actual district-level election results. MSEM enabled us to use actual election results on level 2 as an outcome, which is impossible in conventional MLM since it is restricted to only one level 1 outcome.

In the final example (Schmid, Al Ramiah, & Hewstone, 2014), we were interested in the effects of diversity (both objective—on the social context level of analysis, and subjective—on the individual-level of analysis) on different types of trust using a majority and a minority sample. Moreover, we examined intergroup contact and threat as potential mediators of the effect of diversity on the outcomes. Again, MSEM enabled us to test such a complex multilevel mediation model, which would not be possible with conventional MSEM.

We begin with a short summary of the basics of MLM and discuss the major limitations of conventional MLM. Then, we outline the most important features of MSEM and key advantages compared to conventional MLM. Next, we illustrate and discuss these advantages using three recent examples from our own research. All analyses in these examples were conducted using Mplus, Version 7 (L. K. Muthén & B. O. Muthén, 1998-2015). For these examples, we provide detailed information on the Mplus code and output in the online supplementary material. We point readers interested in additional applications to several excellent introductions to Mplus (Byrne, 2012; Christ & Schlüter, 2012; Geiser, 2013). Moreover, the Mplus manual can be freely downloaded from the webpage of Mplus ([www.statmodel.com](http://www.statmodel.com)).

## **Conventional Multilevel Modeling**

### **When and why do we need multilevel modeling?**

Whenever data are collected at multiple levels of analysis, a hierarchical data structure results. The defining characteristic of a hierarchical data structure is that observations at one level of analysis are nested within observations at a higher-level. Researchers interested in social groups might sample data from multiple individuals from different groups or from different social contexts. In these cases, individuals constitute the level 1 unit of analysis (or in Mplus language, the “within” level), and groups constitute the level 2 unit of analysis (or in Mplus terms, the “between” level). Individuals are thus nested within the group to which they belong.

A hierarchical data structure has two important consequences (for a detailed discussion, see Hoyle, Georgesen, & Webster, 2001; Nezlek, 2001). First, in many cases, level 1 observations are not independent. Single-level analyses like ordinary least squares regression analysis are based on the assumption of independent observations (or, more precisely, independent residuals). Ignoring the hierarchical data structure and, thus, the non-independence of observations often results in biased estimates of standard errors. This, in turn, affects the likelihood of false positive “significant” results, that is, the type 1 error probability (Hox, 2010). Second, single-level analyses, which ignore the hierarchical data structure, often yield misleading results, particularly when results from the group level are interpreted at the individual-level (i.e., ecological fallacy) or vice versa (atomistic fallacy; Pettigrew, 1996).

In multilevel modeling, effects on different levels of analysis are analyzed simultaneously, using a statistical model that accounts for the interdependence of observations due to the nested data structure. Moreover, relations between variables from different levels are analyzed at their appropriate level, thereby avoiding ecological and atomistic fallacies.

### **What is multilevel modeling in statistical terms? A brief introduction**

Assume that a researcher wants to test the hypothesis that intergroup contact reduces prejudice on the individual-level. The researcher collects data from 50 communities

(“groups”) consisting of approximately 50 respondents each. In principal, the researcher’s hypothesis corresponds to a simple regression model, in which prejudice ( $Y$ ) is linearly regressed on contact ( $X$ ) on the individual-level:  $Y = b_0 + b_1 \cdot X + e$ . Central to multilevel modeling is that both regression parameters (the intercept  $b_0$  and the slope  $b_1$ ) are allowed to differ between groups (level 2). This means that both the level of prejudice and the effect of intergroup contact ( $X$ ) on prejudice ( $Y$ ) may differ between communities. Technically speaking, regression parameters at the “lower” (individual) level are modeled as dependent variables at a “higher” (here social context) level. Thus, in a simple multilevel model describing a linear function of  $Y$  on  $X$  (i.e.,  $Y = b_0 + b_1 \cdot X + e$ ), the variation in intercepts ( $b_0$ ) and in slopes ( $b_1$ ) between groups is included; the variation in intercepts is referred to as “random intercept variance” and the variation in slopes is referred to as “random slope variance”. The term “random” means that, in this simple model, these variations are not explained by any predictor variables in the model. They reflect “residuals” at the group level.<sup>1</sup>

A strength of multilevel modeling is that this variation can be modeled and explained by higher-level predictors—a crucial feature for a science of groups (Moritz & Watson, 1998). For instance, a researcher might assume that the level of prejudice differs between communities as a function of group size, that is, the number of people living in these communities (a level-2 variable that may explain some of the random intercept variance). In addition, the researcher might also assume that the effect of intergroup contact on prejudice differs between communities as a function of group size (which implies that the level-2 variable “group size” explains some of the random slope variance). The latter hypothesis is referred to as a cross-level interaction effect (i.e., group size moderates the effect of contact on prejudice).

An example for the first hypothesis is derived from one of our earlier studies (Wagner et al., 2006) employing cross-sectional survey data ( $N = 2,722$ ). Our main focus was the relationship between the proportion of ethnic minorities in a given region (“outgroup

proportion”) and prejudice (see also Example 2 below). Previous research had sometimes found a positive relationship (e.g., Quillian, 1995, 1996), and sometimes a negative relationship (Taylor, 1998) between outgroup proportion and prejudice. Based on intergroup contact theory, we tested whether the mean quantity of intergroup contact within a given region mediated the effect of proportion of ethnic minorities on prejudice.

The survey data available included district codes that indicated the location of residence for each respondent. A ‘district’ is an administrative unit of about 50,000 inhabitants (and with a wide range of possible numerical values). The district codes enabled us to match objective statistical data, such as the proportion of ethnic minorities in the district, to the individual-level data such as quantity of intergroup contact and prejudice levels. Results of MLM showed that the proportion of ethnic minorities in the district and district respondents’ aggregate prejudice level were negatively correlated, meaning that, on average, a higher proportion of ethnic minorities within a district relates to lower prejudice scores of respondents living in this district (for more information about the results, see Wagner et al., 2006).

### **Limitations of Conventional Multilevel Modeling**

Despite the possibilities of MLM, conventional MLM has a number of limitations. Amongst these are the use of only manifest (i.e., observed) variables, the restriction to one level 1 outcome only, and the inability to test more complex models (e.g., models including *multiple* direct and indirect effects).

Just as in ordinary least squares regression, conventional multilevel modeling with manifest variables requires that these variables are measured without error. Violations of this assumption can have serious consequences: measurement error can bias the estimation of regression parameters in conventional MLM (B.O. Muthén & Asparouhov, 2011). Most measures in social psychology contain at least some (random) measurement error. A key advantage of MSEM is the possibility to test measurement models using exploratory and

confirmatory factor analysis at different levels of analysis simultaneously (multilevel exploratory and confirmatory factor analysis; see Example 1 below).

Another limitation of conventional MLM is the restriction to only one level 1 (within-level) outcome variable, although in many cases higher-level (between-level) outcomes can be of interest, too. For instance, outcomes on a group level, such as group performance (Van Kleef, Homan, Beersma, & Van Knippenberg, 2010), or outcomes on a social context level of analysis, such as gross domestic product (e.g., McClelland, 1961), might be of interest. Conventional MLM does not offer the possibility to include such higher-level outcomes.

Snijders and Bosker (2012) differentiated between macro-micro situations and micro-macro situations. In macro-micro situations, the dependent variable is measured at level 1, and predictor variables are measured at level 1 and/or level 2. In micro-macro situations, the outcome variable is measured at level 2, and predictor variables are again measured either at level 1 or level 2. In social psychology, most applications focus on macro-micro situations (Christ, Sibley, & Wagner, 2012; Croon & van Veldhoven, 2007). Likewise, most textbooks on multilevel modeling are restricted to models that are appropriate for investigating macro-micro situations, and most software packages for multilevel modeling (e.g., MLwiN, HLM) are also designed mainly for macro-micro situations. MSEM, however, also allows researchers to investigate micro-macro situations.

Finally, a clear disadvantage of conventional MLM is the inability to test complex models (e.g., models involving multiple direct and indirect effects as well as multiple outcomes; see Example 3 below). For instance, while it is possible in conventional MLM to consider multiple outcomes (i.e., multivariate multilevel modeling; Hox, 2010) *or* to test simple mediation models with a single mediator variable (i.e., one indirect effect; MacKinnon, 2008), more complex models with multiple outcomes *and* multiple indirect effects cannot be tested in a single step, unlike the model shown in Figure 3.

### **Multilevel Structural Equation Modeling**



The aforementioned limitations of conventional MLM are resolved when using MSEM (for recent introductions e.g., Heck & Thomas, 2015; Hox, 2013; Kaplan, 2009) instead of conventional MLM. MSEM combines SEM with MLM and thus combines the best of both worlds (Mehta & Neale, 2005). It allows researchers to develop and test full SEMs at different levels of analysis.

SEM is a general approach that includes both factor and path analysis. A key aspect of SEM is the differentiation between observed (“manifest”) and non-observable (“latent”) variables. The measurement model specifies how latent variables are connected to observed variables (e.g., the latent variable “prejudice” is measured by a number of observed indicators, such as items in a questionnaire). Thus, measurement error can be taken into account by using multiple indicators for each latent variable. The structural model specifies the assumed directional relationships between latent variables.<sup>2</sup>

Multilevel structural equation models (MSEM) apply the advantages of structural equation modeling to multilevel models. First, measurement error can be taken into account by using multiple indicators for each latent variable (see Example 1). Therefore, more accurate estimates of regression parameters are provided compared to conventional MLM. Second, MSEM is not restricted to one level 1 outcome (see Example 2). Multiple outcome variables at different levels of analysis can be modeled simultaneously. Third, complex relationships between variables of interest can be specified and estimated in one step, as is often the case in complex mediation models with multiple mediators and outcomes (see Example 3).

An additional important feature of MSEM is that a measurement model can be tested simultaneously at different levels of analysis (multilevel confirmatory factor analysis; Heck & Thomas, 2015; B. O. Muthén, 1991). For instance, multilevel confirmatory factor analysis can be used to assess the invariance of the measurement model across levels. The basic question here is whether the respective indicators represent the same underlying constructs at different

levels of analysis (for more information on testing for measurement invariance in MSEM, see Jak, Oort, & Dolan, 2014). This is typically assumed when conventional MLM is used, an assumption that, when not met, can have serious consequences. Zyphur, Kaplan, and Christian (2008) provide a thorough discussion on measurement invariance issues in multilevel modeling. Moreover, since the factorial structure on level 2 is often unknown because of a simple aggregation of individual measures (e.g., van de Vijver & Poortinga, 2002), multilevel exploratory factor analysis can be used to explore the factorial structure on higher-levels of analysis (see Example 1 below).

Finally, model fit can be evaluated with the same fit measures known from the SEM framework (Kline, 2016), including the comparative fit index (CFI), the root mean square error of approximation (RMSEA), and the standardized root mean square residual (SRMR). This is a further advantage compared to conventional MLM, where only relative model fit (i.e., comparing models with a different number of predictor variables) can be assessed (Hox, 2010).

Though MSEM is still relatively new, it is now more readily accessible to researchers due to recent developments in estimation techniques and statistical software (for an overview, see Kaplan, Kim, & Kim, 2009). For instance, the MSEM approach implemented in Mplus (e.g., Asparouhov & B.O. Muthén, 2007) offers researchers a comfortable platform to specify and test complex models at multiple levels of analysis. In all our examples, we implemented MSEM using Mplus. There are also alternative software packages available that can be used for MSEM including LISREL, R (package *xxM*), or STATA.

In the following paragraphs, we provide three examples<sup>4</sup> of MSEM from our own research. In the first example (Christ et al., 2014), we used MSEM to test the contextual effect of intergroup contact on outgroup prejudice. Using MSEM has clear advantages compared to conventional MLM when it comes to testing contextual effects (Lüdtke et al., 2008). In the second example, we used MSEM for a level 2 outcome variable (Green et al., 2016). In the

third example, we used MSEM to test a complex multilevel mediation model (Preacher, Zyphur, & Zhang, 2010) with multiple indirect effects as well as multiple outcomes (Schmid et al., 2014) that we would not have been able to test (in a single step) with conventional MLM.

### **Example 1: Use of Latent Instead of Manifest Variables**

In the first example (Christ et al., 2014), we were interested in the contextual effect of intergroup contact on outgroup prejudice. A contextual effect is present whenever the aggregate of an individual-level variable has an effect on the outcome variable even after controlling for the effect of the individual level variable (Raudenbush & Bryk, 2002). In other words, a contextual effect occurs when there is a difference between the individual level and group-level effect of an individual-level variable. In our case, we tested the difference between the effect of intergroup contact on the level of social contexts (the group or “between” level effect) and the effect of individual-level contact within contexts (the individual or “within” level effect) on prejudice (see Figure 1). A contextual effect of intergroup contact would mean that intergroup contact at the social context level predicts individuals’ prejudice over and above the amount of individual-level contact, and that the processes involved cannot be reduced to characteristics of individuals or specific situations in which intergroup contact occurs. A social context level effect of intergroup contact on individual prejudice could, for instance, indicate that the estimated individual prejudice is lower in regions in which people have more contact experiences on average—independent of how much contact experiences individuals have themselves.

A contextual effect can be estimated with conventional MLM (see Raudenbush & Bryk, 2002 for details). However, this can be problematic because in conventional MLM, the group mean (i.e., the mean in level 1 variables within each level 2 unit) is used to estimate the “between” level effect. Yet sampling error in the group mean can cause biased and less accurate estimates of the “true” contextual effect. One way to overcome this problem is to use

MSEM as implemented in Mplus (see Lüdtke et al., 2008). With MSEM, a so-called multilevel latent covariate (MLC) approach can be used that corrects for the unreliability in the level 2 construct. The group mean is treated as a latent variable (for details, see Lüdtke et al., 2008), resulting in unbiased estimates of the level 2 effect and, thus, the contextual effect. We implemented the MLC approach (see Figure 1 and online supplementary material for the Mplus syntax) and found a significant contextual effect of intergroup contact on outgroup prejudice in all studies reported, although effects were relatively small in size (effect sizes of the contextual effect [ES2; see Marsh et al., 2009] of contact ranged from .21 to .35).<sup>5</sup> The specification of the contextual effect in the Mplus syntax (see online supplementary material) is included directly underneath the command “model constraint” in the model command block. In this part of the model specification, a new parameter (“context”) is defined that reflects the difference between the between-level and within-level effects of intergroup contact on prejudice. The estimate for this new parameter can be found in the Mplus output under the heading “New/Additional Parameters” with  $-.282, p < .001$ .

We also tested whether this contextual effect was explained in terms of more positive social norms at the social context level, and our results indeed provided evidence for this (for a detailed description of the results see Christ et al., 2014). As an indicator for social norms, we used a measure of diversity beliefs, which reflect the extent to which individuals value and endorse diversity (Tropp & Bianchi, 2006). When estimated at level 2 (e.g., the neighborhood level) as a random effect, involving the average aggregate level of diversity beliefs, we deemed this measure to reflect social norms in the neighborhood. In order to establish the factorial structure of our norms and prejudice measures on the individual and social context levels simultaneously we used multilevel exploratory factor analysis (ML-EFA) as implemented in Mplus, using data from Study 1a in Christ et al. (2014). In Mplus, ML-EFA is based on maximum likelihood estimates, allowing us to compare different factorial solutions by means of fit statistics known from the structural equation modeling framework. The two

within- and two between-factor solutions (involving separate factors of diversity beliefs and prejudice on both levels, respectively) showed the best fit to the data compared to all other possible combinations). In the online supplementary material, the Mplus syntax is shown for the ML-EFA. We also provide the syntax for a multilevel confirmatory factor analysis with two separate factors for diversity beliefs and prejudice on both the within and between-level.

Defining and testing measurement models is, as discussed above, an important additional feature of MSEM, enabling researchers to test for measurement invariance (or difference) on different levels of analysis, and thus provides the opportunity to confirm and develop multilevel theories. A more thorough discussion of multilevel factor analysis can be found in Heck and Thomas (2015; see Chapter 6).

### **Example 2: Level 2 Outcome Variable**

In our second example, we examined whether the proportion of stigmatized immigrants is associated with voting for radical right-wing parties, via threat perceptions and positive intergroup contact in Switzerland. We assumed that the proportion of stigmatized immigrants increases both threat perceptions and contact opportunities, which in turn should respectively heighten and attenuate voting for parties on the far right of the political spectrum (see Figure 2). As an indicator of radical right-wing voting, we used actual election results at the district level (i.e., level 2). Thus, we were able to test a micro-macro link, such that the relation between individual threat perceptions and contact experiences as predictor variables were measured at level 1 while the level 2 outcome variable was based on the actual election results. Figure 2 presents the tested MSEM; the accompanying Mplus syntax is given in the online supplementary material.

Results of MSEM (see online supplementary material for the corresponding estimates under the headings “Between Level” and „Total, Total Indirect, Specific Indirect, and Direct Effect”) showed that the proportion of stigmatized immigrants heightened threat perceptions, which, in turn, increased actual radical right-wing voting via an increased willingness to vote

for right-wing parties (see estimate for the specific indirect effect of proportion of immigrants on actual right-wing voting via threat and willingness to vote right-wing parties,  $AV\ VP\ T\ I: .742, p = .025$ ). Positive intergroup contact—albeit unrelated to immigrants’ presence—was associated with *reduced* radical right-wing voting through an attenuated willingness to vote for right-wing parties (i.e., voting propensity on level 1) and reduced threat (see estimate for the total indirect effect of intergroup contact on actual right-wing voting,  $-19.229, p < .001$ ). For a detailed discussion of the results we refer to the original paper by Green et al. (2016).

Conventional multilevel models are restricted to applications where the dependent variable is measured at level 1, such as individual attitudes or behaviors. Although individual outcome variables are of main concern in psychology when studying individuals nested in groups and/or groups nested in their social environment, level 2 outcomes like group performance or actual voting results are equally important. MSEM allows researchers to include higher-level outcome variables in the model (Lüdtke et al., 2008), thus permitting tests of micro-macro links (as well as macro-micro links). Thus, MSEM can be conveniently used to estimate multilevel models capturing micro-macro situations as we have demonstrated in Example 2.

### **Example 3: Multilevel Mediation**

Our final example (Schmid et al., 2014) deals with multilevel mediation. In this paper, we were interested in the effects of diversity on a social context level (in this case, the proportion of ethnic outgroup members in a neighborhood) on social trust. While some authors argue that growing diversity has negative consequences for trust (e.g., Putnam, 2007), partly because it evokes more threat (e.g., Blalock, 1967; Bobo, 1999), other scholars have argued and found that greater diversity provides more opportunities for contact (e.g., Wagner et al., 2006) and therefore might lead to higher, not lower, trust.

We examined the effects of neighborhood ethnic diversity on three different types of trust—outgroup, ingroup, and neighborhood trust—as well as on outgroup attitudes, and

tested both direct and indirect (via intergroup contact and perceived threat) effects on these different types of trust and outgroup attitudes (see Figure 3). Moreover, we tested these effects among White British majority and ethnic minority respondents. The results of our study are not in line with Putnam's (2007) claim that neighborhood diversity had a negative effect on trust, because we did not obtain any negative total effects of actual diversity at the neighborhood level, neither for the majority nor the minority group. In Figure 3, the tested multilevel mediation model is presented; the accompanying Mplus syntax is given in the online supplementary material. Estimates for the total effects of diversity on the different types of trust can be found in the Mplus output presented in the online supplementary material under the heading "Total, total indirect, specific indirect, and direct effects". For instance, the estimate for the total effect of diversity on outgroup trust is .152,  $p = .061$ . For a detailed discussion of the specific results, we refer to the original paper of Schmid et al. (2014).

In the case of multiple levels of analysis, numerous multilevel mediation designs can be distinguished depending on the level at which the independent variable, the mediator variable and the dependent variable, respectively, are measured (Preacher et al., 2010). In conventional MLM, only 1-1-1 (all variables measured at the within-level), 2-1-1, and 2-2-1 multilevel mediation designs can be tested (Preacher et al., 2010), using standard single-level procedures (i.e., a two-step approach) to establish mediational effects (Krull & MacKinnon, 2001). However, designs including a level 2 mediator or a level 2 outcome (e.g., 1-2-1, 1-2-2) cannot be tested with conventional MLM since level 2 outcomes are not permitted.

Moreover, the aforementioned standard procedures are only appropriate for a 1-1-1 design when fixed-effect models are estimated. As Kenny, Korchmaros, and Bolger (2003) emphasized, it becomes more complicated when effects are considered to be random: If the mediational links vary across level 2 units, the random effects for the independent variable-mediator link and for the mediator-dependent variable link can be correlated. The problem for lower-level mediation models using conventional MLM is, however, that random effects

cannot be estimated in one step; therefore, the covariance between random effects cannot be directly estimated. As shown by Kenny et al. (2003), the formulae for the indirect effect and its standard error have to be modified to include the covariance between the random effects. Bauer, Preacher, and Gil (2006) recently presented direct procedures to test random indirect effects in lower-level mediation models with conventional MLM; however, these procedures are not yet commonly used in the science of groups.

Again, MSEM has the potential to directly test lower-level mediation models with random effects (Mehta & Neale, 2005; Preacher, Zhang, & Zyphur, 2011). Moreover, all possible multilevel mediation designs including level 2 mediators and outcomes can be tested using MSEM. Thus, MSEM has clear advantages compared to conventional MLM.

### **Practical Issues**

In the following section, we address some general practical issues that have to be considered when using MSEM. Due to space constraints, we are unable to go into the technical details underlying these issues, but we refer interested readers to additional references and online resources at the end of this section.

#### **Sample Size**

As in MLM, sample size, especially at level 2 and higher (Snijders, 2005), is a critical issue in MSEM. At all levels, an adequate sample size is needed in order to obtain unbiased estimates of model parameters and to ensure sufficient statistical power. Simulation studies have shown that for MLM, sample sizes of 50 (ideally 100) are needed at level 2 in order to get unbiased estimates of fixed effects and of their respective standard errors (Maas & Hox, 2005).

Results of a simulation study by Meuleman and Biellel (2009) have shown that sufficient sample size depends on the specific interests of the researcher (e.g., whether the focus is on the level 2 factor structure vs. whether one is interested in the structural effects on level 2), the expected effect sizes, and the complexity of the estimated model. For simple between-level models (i.e., models involving a small number of indicators, only one structural effect, and no



interactions), Meuleman and Bielle (2009) proposed the following guidelines: If only the between-level factor structure is of interest, a group sample size of 40 is sufficient. For large ( $> 0.50$ ) structural effects at the between-level, 60 groups are required. For smaller effects, more than 100 groups are needed. And as the between-level model becomes more complex, substantially larger level 2 sample sizes are needed. One of the main obstacles to applying MSEM thus tends to be not having samples of sufficient size.

However, a simulation study by Hox, van de Schot, and Matthijsse (2012) has shown that Bayesian estimation methods instead of the typically used estimation methods (i.e., maximum likelihood, Weighted Least Square) can (partly) help to overcome this limitation. At least for simple models (e.g., when, at both the individual and the social context level, the model consists of a latent variable with four indicators and a structural effect from an observed exogenous variable on the latent variable), sample sizes of only 20 at the social context level seem to be sufficient for accurate Bayesian estimation. Having said this, although Bayesian estimation allows for smaller sample sizes, power may nonetheless remain a problem. Thus, the general recommendation is still to obtain as large a sample size as possible at level 2 and higher.

### **Model fit**

One of the advantages of MSEM compared to MLM is the availability of overall-model-test statistics (i.e., chi-square test) that help judge exact model fit, and descriptive fit indices (e.g., CFI, RMSEA, SRMR) that assess the goodness of fit of a model according to a set of indicators. Model fit is a central concern when applying MSEM making it imperative to know how to evaluate model fit. In SEM, although cut-off values for different fit indices have been proposed (e.g., Hu & Bentler, 1999), these “golden rules” have been criticized since “broad generality across different conditions and sample sizes” (Marsh, Hau, & Wen, 2004, p. 321) is not statistically appropriate. The same applies to MSEM.

Moreover, most of the fit measures are only available for the entire model, i.e., including both the model on level 1 (within-level) as well as the model on level 2 (between-

level). This is problematic for two reasons (Ryu, 2014). First, because of the typically small sample size at the higher-level of the model, the CFI and RMSEA might not be sensitive enough to detect a lack of fit in the higher-level model. Second, when the general fit measures indicate poor model fit, it is not clear at which level the model does not fit well. Thus, it is important to assess model fit separately for the within and the between-level model. In Mplus, the SRMR is available for both levels of analysis (SRMR<sub>within</sub> and SRMR<sub>between</sub>). Results of a simulation study have shown that the SRMR<sub>between</sub> was able to detect model misspecification in the between-model (Hsu, Kwok, Lin, & Acosta, 2015). Moreover, there are additional ways to obtain fit measures for both levels of analysis separately (Ryu, 2014). However, results of a further simulation study showed that all level-specific fit indices are sensitive to the size of the intra-class correlation (ICC) with a drop in performance with lower ICCs (Hsu, Lin, Kwok, Acosta, & Willson, 2016). In sum, more research is needed and researchers should thus be cautious when interpreting model fit.

### **Software, Books, and Online Resources for MSEM**

#### **Software for MSEM**

*Mplus*. Powerful commercial software package with a lot of additional information (e.g., papers using MSEM, syntax codes) provided on their webpage (see below).

*LISREL*. Commercial software package for structural equation modeling that offers the possibility to fit MSEM (<http://www.ssicentral.com/lisrel/>).

*R*. R is a language and environment for statistical computing and graphics and is freely available (<https://www.r-project.org/>). MSEM can be implemented in R using the package *xxM* (<http://xxm.times.uh.edu/>).

*STATA*. Powerful commercial software package (<http://www.stata.com/>). MSEM can be implemented with either GSEM (<http://www.stata.com/features/overview/generalized-sem/>) or GLLAMM (<http://www.gllamm.org/>).

#### **Helpful Books and Online Resources.**

Byrne, B.M. (2012). *Structural equation modeling with Mplus: Basic concepts, applications, and programming*. New York: Taylor & Francis Group.

Introduction to structural equation modeling using Mplus. Very helpful for beginners in both SEM and Mplus.

Heck, R.H. & Thomas, S.L. (2015). *An introduction to multilevel modeling techniques: MLM and SEM approaches using Mplus* (3rd ed.). New York: Routledge.

Very good (non-technical) introduction to MLM and MSEM including syntax code for Mplus.

<http://quantpsy.org/>

Webpage of Kristopher J. Preacher who published (amongst other things) a number of articles on MSEM (e.g., multilevel mediation using MSEM). He provides via the webpage supplemental material for his publications (e.g., Mplus syntax code for different multilevel mediation models with or without random effects).

<http://statmodel.com/>

Webpage of the Mplus software with example inputs for MSEM and a collection of technical and applied papers on MSEM (<http://statmodel.com/papers.shtml>). Users of Mplus can consult the Mplus discussion list for any questions on model specification using Mplus (<http://statmodel.com/cgi-bin/discus/discus.cgi>).

### **Discussion**

A science of groups and individuals nested in groups needs to account for different levels of analysis since only multilevel perspectives provide a complete and realistic picture of processes that occur within and between social groups (Pettigrew, 2006). A multilevel perspective requires, however, appropriate statistical models. Conventional MLM is a well-known statistical method to handle data from different levels of analysis that is becoming

more frequently used in group research (e.g., Allen, Jones, & Sheffield, 2009; Kivlighan, Li, & Gillis, 2015; Paquin, Kivlighan, & Drogosz, 2013; Thorgeirsdottir, Bjornsson, & Ankelsson, 2015). However, conventional MLM has a number of limitations that researchers should be aware of. Amongst these limitations are (a) unreliability issues in manifest variables, (b) the restriction to a single-level 1 outcome only, and (c) the inability to test models with multiple direct and indirect effects (e.g., multilevel mediation models).

In the present article, we introduced MSEM as a promising methodological development that helps overcome these limitations. Specifically, MSEM offers the possibility to use latent instead of manifest variables and can therefore take measurement error into account. Moreover, the measurement model can be tested on both the within and between-level of analysis. It enables researchers to specify level 2 outcome variables and allows them to test complex multilevel mediation models including multiple direct and indirect effects (Preacher et al., 2010).

Because MSEM is relatively new there are still some unresolved issues and further developments are to be expected. However, MSEM is now a method that is more easily accessible to researchers because of recent developments in estimation techniques and statistical software (Heck & Thomas, 2015). For instance, the MSEM approach implemented in Mplus (e.g., Asparouhov & B.O. Muthén, 2007) offers researchers a comfortable platform to specify and test complex models at multiple levels of analysis. We have provided three examples of MSEM using this approach to illustrate (1) how to analyze contextual effects, (2) how to model micro-macro situations (i.e., level 2 outcomes) appropriately, and (3) how to test complex multilevel mediation models (for additional applications in group research, see Ozeki, 2015; Petitta, Jiang, & Palange, 2015).

Yet MSEM offers even more possibilities than those presented in our examples. Muthén and Asparouhov (2011), for example, provide an overview of additional variants of MSEM (e.g., two-level exploratory factor analysis; multilevel growth mixture modeling).

Using Bayesian methodology further expands the possibilities of MSEM (Asparouhov & Muthén, 2015). Moreover, Bayesian estimation methods have the advantage of requiring smaller sample sizes on level 2 (or level 3) compared to maximum likelihood estimation or weighted least squares (WLS) estimation methodology that are typically used in MSEM (Hox et al., 2012).

To conclude, our goal in this paper was to highlight the importance of MSEM as an analytical technique for a science of groups. Since MSEM has several key advantages compared to conventional MLM, we hope that our paper will stimulate researchers interested in group phenomena to adopt this technique more widely, to simultaneously analyze information on different levels of analysis.

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## Notes

1 It is beyond the scope of this article to present the statistical basics of MLM; however, there exist a number of excellent and detailed introductions to MLM (e.g., Hox, 2010; Kreft & de Leeuw, 1998; Raudenbush & Bryk, 2002; Snijders & Bosker, 2012). Moreover, there are several articles and chapters describing the application of multilevel analysis to group research more generally (Christ, Sibley, & Wagner, 2012; Nezlek & Zyzanski, 2008).

2 Although Croon and Veldhoven (2007) developed an approach for handling higher-level outcomes outside of the MSEM framework we will introduce below a recent simulation study showing the superiority of MSEM (Lüdtke et al., 2008).

3 Again, it is not our aim here to present a detailed introduction to SEM. With regard to MLM, there are a number of excellent introductions to SEM (e.g., Kline 2016; Schumacker & Lomax, 2009).

4 For the present purposes, we used simplified versions of the models (e.g., omitting control variables) compared to those in the original publications. Therefore, results based on the model inputs presented in the online supplementary material differ slightly from those in the original publications.

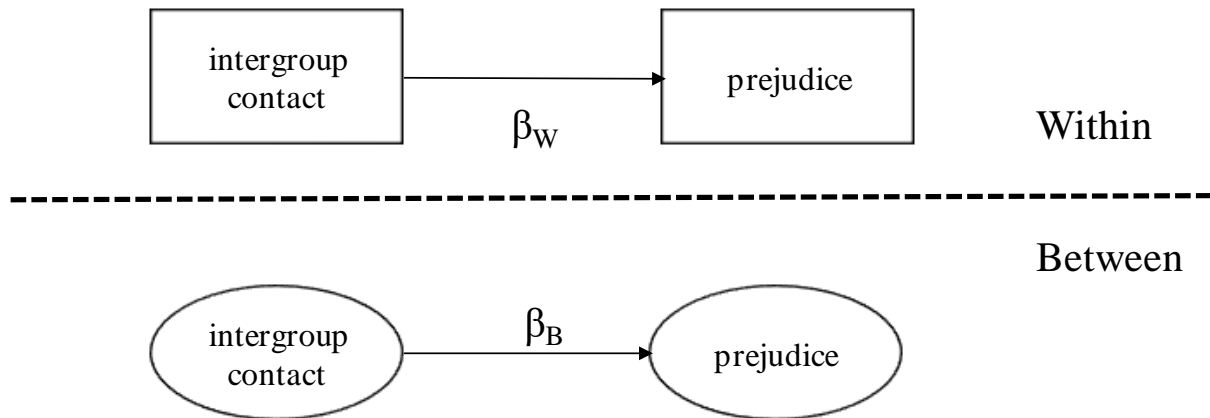
5 Lüdtke, Marsh, Robitzsch, and Trautwein (2011) demonstrated that the estimation of contextual effects may not only be biased due to sampling error, but also due to measurement error. They distinguished between different approaches to correct for sources of error in estimating contextual effects, and proposed a 2×2 taxonomy of multilevel contextual models correcting for no error source, for only one source of error, or for all error sources. Lüdtke et

al. (2011) showed in a simulation study that, depending on specific data circumstances, the uncorrected and the partial correction approaches can result in biased estimates of the contextual effect. However, when the data provides only limited information on the level 2 constructs (i.e., small number of groups, low intraclass correlations), partial correction approaches outperform the doubly latent approach. The authors therefore suggest that researchers juxtapose the different approaches (where possible) and use the estimates from the different approaches as bounds for the true parameter. We were able to use a so-called doubly latent contextual model in one of our studies (Study 1b in Christ et al., 2014) since multiple items for intergroup contact and prejudice were available and therefore latent variables on both levels could be specified. Results of the different multilevel contextual models confirmed the contextual effect of intergroup contact.

Figure 1.

MSEM using the MLC approach for testing the contextual effect of intergroup contact

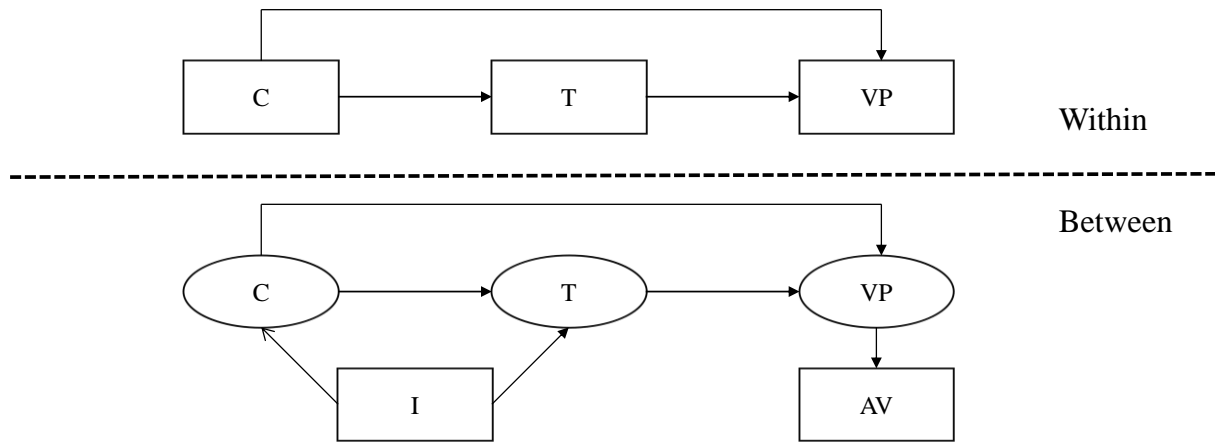
(Example 1)



Note. The contextual effect is the difference between  $\beta_B$  and  $\beta_W$ . In Mplus, this difference can be defined as a new model parameter with the corresponding test statistic (see online supplementary material).

Figure 2.

MSEM for using a level 2 outcome variable (Example 2)

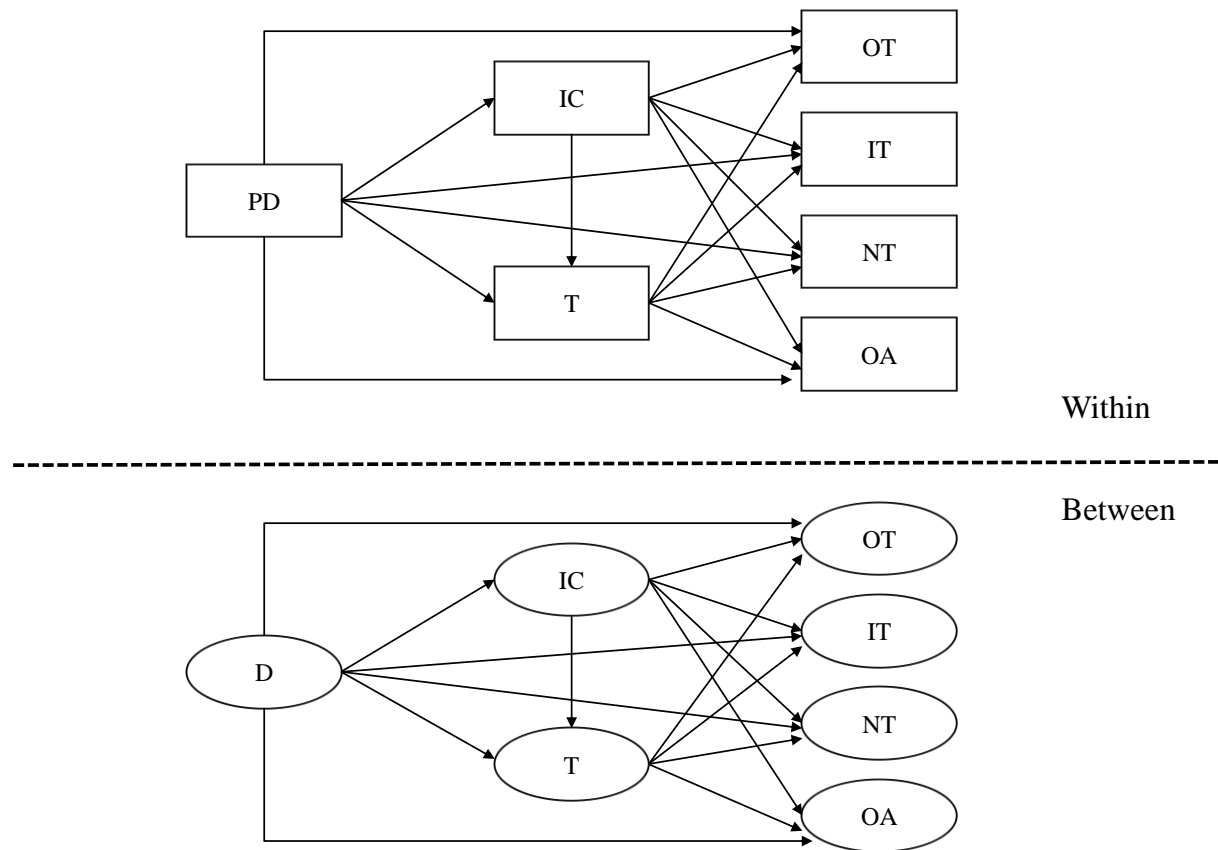


Note. I = % of stigmatized immigrants; C = positive contact with stigmatized immigrants; T = perceived threat; VP = SVP voting propensity; AV = actual SVP vote



Figure 3.

MSEM for testing a complex multilevel mediation model (Example 3)



Note. PD = perceived diversity; D = Objective diversity; C = intergroup contact; T = threat; OT = outgroup trust; IT = ingroup trust; NT = neighborhood trust; OA = outgroup attitudes

## Online Supplementary Material

All Mplus input files and data (in ASCII-format) for the three examples can be downloaded. In the following, the annotated Mplus code as well as excerpts from the Mplus output for all three examples are provided.

### Example 1

#### Mplus code (Mplus input file) and excerpts from the Mplus output for the MLC approach

```
Title:      Contextual effect of contact - MLC approach

Data:      FILE IS example1.dat; !text file containing raw data in wide format

VARIABLE:  NAMES ARE kreis con1 con2 con3 prej1 prej2 prej3 con prej;
           USEVARIABLES ARE con prej;
           MISSING ARE ALL (9 99); !missing data denoted "9" oder "99" in example1.dat
           CLUSTER IS kreis; !Level 2 group identifier

ANALYSIS:  TYPE = TWOLEVEL; !tell Mplus to perform multilevel modeling

MODEL:     !model specification follows (see Figure 1)
           %WITHIN% !Model for within effects follows
           prej ON con (b_within); !specifying the within effect of contact on prejudice;
                               !call the within effect b_within
           con (Psi_W); !call the within variance in con Psi_W
           prej (Theta_W); !call the within variance in prej Theta_W

           %BETWEEN%
           prej ON con (b_betwn); !specifying the between effect of contact on prejudice;
                               !call the between effect b_betwn
           con (Psi_B); !call the between variance in con Psi_B
           prej (Theta_B); !call the between variance in prej Theta_B

           MODEL CONSTRAINT: !section for computing the contextual effect and effect size
           new(context); !name the contextual effect
           context = b_betwn - b_within; !compute the contextual effect

           new(ES2); !name the effect size for the contextual effect
           Es2= context*(2*sqrt(Psi_B)/sqrt(Psi_W*b_within**2 + Theta_W)); !compute the effect
                               !size (Marsh et al., 2009)
```

#### Excerpts from the Output

```
MODEL RESULTS !Model results follow

                                Estimate      S.E.  Est./S.E.      Two-Tailed
                                P-Value

Within-level !Results on the within-level

!Within effect of contact on prejudice
PREJ      ON
CON              -0.415      0.023      -18.408      0.000

Variances
CON              0.477      0.013      36.159      0.000

Residual Variances
PREJ            0.572      0.015      37.784      0.000

Between-level !Results on the between-level

!Between effect of contact on prejudice
PREJ      ON
CON              -0.697      0.058      -11.973      0.000
```

Means				
CON	2.153	0.022	97.024	0.000
Intercepts				
PREJ	3.796	0.127	29.792	0.000
Variances				
CON	0.108	0.011	9.987	0.000
Residual Variances				
PREJ	0.004	0.006	0.731	0.465
New/Additional Parameters	!Estimates for the contextual effect and the effect size			
CONTEXT	-0.282	0.069	-4.081	0.000
ES2	-0.230	0.055	-4.137	0.000

## Mplus code (Mplus input file) and excerpts from the Mplus output for the doubly latent approach

```

Title:      Contextual effect of contact - doubly latent approach

Data:      FILE IS example1.dat; !text file containing raw data in wide format

VARIABLE:  NAMES ARE kreis con1 con2 con3 prej1 prej2 prej3 con prej;
           USEVARIABLES con1 con2 con3 prej1 prej2 prej3;
           MISSING ARE ALL (9 99); !missing data denoted "9" oder "99" in example1.dat
           CLUSTER IS kreis; !Level 2 group identifier

ANALYSIS:  TYPE = TWOLEVEL; !tell Mplus to perform multilevel modeling

MODEL:     !model specification follows
           %WITHIN% !Model for within part follows
           contactw BY con1 !Measurement model for intergroup contact on Level 1
           con2 (1) !parameters with same number are constraint to be equal
           con3 (2);

           prejwt BY prej1 !Measurement model for prejudice on Level 1
           prej2 (3)
           prej3 (4);

           prejwt ON contactw (b_within); !specifying the within effect of contact on prejudice;
                                           !call the within effect b_within
           %BETWEEN% !Model for between part follows
           contactb BY con1 !Measurement model for intergroup contact on Level 2

           con2 (1)
           con3 (2);

           prejb BY prej1 !Measurement model for prejudice on Level 2
           prej2 (3)
           prej3 (4);

           prejb ON contactb (b_betwn); !specifying the between effect of contact on prejudice;
                                           !call the between effect b_betwn
           MODEL CONSTRAINT: !section for computing the contextual effect
           new(context); !name the contextual effect
           context = b_betwn - b_within; !compute the contextual effect

```

## Excerpts from the Output

```

MODEL RESULTS !Model results follow

              Estimate      S.E.  Est./S.E.      Two-Tailed
              P-Value

Within-level !Results on the within-level

!Results for the measurement model (factor loadings)
CONTACTW BY
  CON1      1.000      0.000      999.000      999.000
  CON2      1.441      0.051      28.326       0.000
  CON3      1.540      0.056      27.694       0.000

```

```

PREJW    BY
  PREJ1      1.000    0.000   999.000   999.000
  PREJ2      0.740    0.023    32.143    0.000
  PREJ3      0.896    0.024    37.329    0.000

!Within effect of contact on prejudice
PREJW      ON
  CONTACTW   -0.857    0.053   -16.038    0.000

Variances
  CONTACTW   0.194    0.012    16.380    0.000

Residual Variances
  CON1       0.255    0.012    22.054    0.000
  CON2       0.507    0.022    23.207    0.000
  CON3       0.452    0.023    19.663    0.000
  PREJ1      0.299    0.020    14.639    0.000
  PREJ2      0.450    0.019    23.735    0.000
  PREJ3      0.333    0.018    18.454    0.000
  PREJW      0.543    0.027    20.223    0.000

Between-level !Results on the between-level

!Results for the measurement model (factor loadings)
CONTACTB BY
  CON1       1.000    0.000   999.000   999.000
  CON2       1.441    0.051    28.326    0.000
  CON3       1.540    0.056    27.694    0.000

PREJB    BY
  PREJ1      1.000    0.000   999.000   999.000
  PREJ2      0.740    0.023    32.143    0.000
  PREJ3      0.896    0.024    37.329    0.000

!Between effect of contact on prejudice
PREJB      ON
  CONTACTB   -1.089    0.098   -11.134    0.000

Intercepts
  CON1       1.792    0.019    93.474    0.000
  CON2       2.067    0.028    72.839    0.000
  CON3       2.600    0.026    98.589    0.000
  PREJ1      2.529    0.024   103.730    0.000
  PREJ2      2.061    0.020   100.900    0.000
  PREJ3      2.302    0.024    97.337    0.000

Variances
  CONTACTB   0.059    0.007     8.535    0.000

Residual Variances
  CON1       0.003    0.003     0.849    0.396
  CON2       0.023    0.009     2.530    0.011
  CON3       0.001    0.006     0.249    0.803
  PREJ1      0.017    0.006     2.964    0.003
  PREJ2      0.000    0.005     0.079    0.937
  PREJ3      0.005    0.006     0.826    0.409
  PREJB      0.004    0.008     0.471    0.638

New/Additional Parameters !Estimate for the contextual effect
  CONTEXT    -0.232    0.117    -1.976    0.048

```

## Mplus code (Mplus input file) and excerpts from the Mplus output for the ML-EFA

```

Title:      Multilevel EFA

Data:      FILE IS example1.dat; !text file containing raw data in wide format

VARIABLE:  NAMES ARE kreis con1 con2 con3 prej1 prej2 prej3 con prej;
           USEVARIABLES ARE con1 con2 con3 prej1 prej2 prej3;
           MISSING ARE ALL (9 99); !missing data denoted "9" oder "99" in example1.dat
           CLUSTER IS kreis; !Level 2 group identifier

ANALYSIS:  TYPE = TWOLEVEL EFA 1 2 1 2; ! !tell Mplus to perform multilevel EFA
           !1 2 1 2: On both levels, one and two factors are extracted.
           !All combinations will be computed (1 factor within/1 factor between;

```

```
!2 factors within/1 factor between; 1 factor within/2 factors between;
!2 factors within/2factors between)
```

## Excerpts from the Output

```
!Results for the solution with 2 within and 2 between factors
EXPLORATORY FACTOR ANALYSIS WITH 2 WITHIN FACTOR(S) AND 2 BETWEEN FACTOR(S):
```

```
MODEL FIT INFORMATION !Information on model fit
```

```
Number of Free Parameters          40
```

```
Loglikelihood
```

```
      H0 Value          -19104.431
      H1 Value          -19101.185
```

```
Information Criteria
```

```
      Akaike (AIC)          38288.861
      Bayesian (BIC)        38525.226
      Sample-Size Adjusted BIC 38398.133
      (n* = (n + 2) / 24)
```

```
Chi-Square Test of Model Fit
```

```
      Value          6.491
      Degrees of Freedom      8
      P-Value          0.5924
```

```
RMSEA (Root Mean Square Error Of Approximation)
```

```
      Estimate          0.000
```

```
CFI/TLI
```

```
      CFI          1.000
      TLI          1.001
```

```
Chi-Square Test of Model Fit for the Baseline Model
```

```
      Value          5328.318
      Degrees of Freedom     30
      P-Value          0.0000
```

```
SRMR (Standardized Root Mean Square Residual)
```

```
      Value for Within          0.005
      Value for Between          0.014
```

```
WITHIN-LEVEL RESULTS !Results on Level 1 (only factor loadings and factor correlations)
```

```
GEOMIN ROTATED LOADINGS (* significant at 5% level)
```

	1	2
CON1	0.655*	0.014
CON2	0.621*	-0.046
CON3	0.741*	0.000
PREJ1	0.029	0.872*
PREJ2	-0.071*	0.630*
PREJ3	-0.008*	0.770*

```
GEOMIN FACTOR CORRELATIONS (* significant at 5% level)
```

	1	2
1	1.000	
2	-0.434*	1.000

```
BETWEEN-LEVEL RESULTS !Results on Level 2 (only factor loadings and factor correlations)
```

```
GEOMIN ROTATED LOADINGS (* significant at 5% level)
```

	1	2
CON1	-0.904*	0.215
CON2	-0.793*	0.414
CON3	-0.996*	-0.003
PREJ1	0.937*	0.140
PREJ2	1.001*	0.024
PREJ3	0.929*	-0.173

GEOMIN FACTOR CORRELATIONS (\* significant at 5% level)

	1	2
1	1.000	
2	-0.272	1.000

	1	2
1	1.000	
2	-0.272	1.000

## Mplus code (Mplus input file) and excerpts from the Mplus output for the ML-CFA

```
Title:      Multilevel CFA

Data:      FILE IS example1.dat; !text file containing raw data in wide format

VARIABLE:  NAMES ARE kreis con1 con2 con3 prej1 prej2 prej3 con prej;
           USEVARIABLES con1 con2 con3 prej1 prej2 prej3;
           MISSING ARE ALL (9 99); !missing data denoted "9" oder "99" in example1.dat
           CLUSTER IS kreis; !Level 2 group identifier

ANALYSIS:  TYPE = TWOLEVEL; !tell Mplus to perform multilevel modeling

MODEL:     !model specification follows
           %WITHIN% !Model for within part follows
           contactw BY con1 !Measurement model for intergroup contact on Level 1
           con2 (1) !parameters with same number are constraint to be equal
           con3 (2);

           prejw BY prej1 !Measurement model for prejudice on Level 1
           prej2 (3)
           prej3 (4);

           %BETWEEN% !Model for between part follows
           contactb BY con1 !Measurement model for contact on Level 2
           con2 (1)
           con3 (2);

           prejb BY prej1 !Measurement model for prejudice on Level 2
           prej2 (3)
           prej3 (4);
```

## Excerpts from the Output

```
MODEL FIT INFORMATION !Information on model fit

Number of Free Parameters                28

Loglikelihood

      H0 Value                        -19129.536
      H0 Scaling Correction Factor      1.0345
      for MLR
      H1 Value                        -19101.185
      H1 Scaling Correction Factor      0.9522
      for MLR

Information Criteria

      Akaike (AIC)                    38315.073
      Bayesian (BIC)                  38480.528
      Sample-Size Adjusted BIC        38391.563
      (n* = (n + 2) / 24)

Chi-Square Test of Model Fit

      Value                            67.753*
      Degrees of Freedom                20
```

P-Value	0.0000
Scaling Correction Factor for MLR	0.8369

\* The chi-square value for MLM, MLMV, MLR, ULSMV, WLSM and WLSMV cannot be used for chi-square difference testing in the regular way. MLM, MLR and WLSM chi-square difference testing is described on the Mplus website. MLMV, WLSMV, and ULSMV difference testing is done using the DIFFTEST option.

RMSEA (Root Mean Square Error Of Approximation)

Estimate	0.030
----------	-------

CFI/TLI

CFI	0.991
TLI	0.986

Chi-Square Test of Model Fit for the Baseline Model

Value	5305.244
Degrees of Freedom	30
P-Value	0.0000

SRMR (Standardized Root Mean Square Residual)

Value for Within	0.017
Value for Between	0.031

MODEL RESULTS !Model results follow

	Estimate	S.E.	Est./S.E.	Two-Tailed P-Value
Within-level !Results for the measurement models on Level 1 follow				
CONTACTW BY				
CON1	1.000	0.000	999.000	999.000
CON2	1.441	0.051	28.219	0.000
CON3	1.540	0.056	27.506	0.000
PREJW BY				
PREJ1	1.000	0.000	999.000	999.000
PREJ2	0.740	0.023	32.135	0.000
PREJ3	0.896	0.024	37.300	0.000
PREJW WITH				
CONTACTW	-0.166	0.011	-15.179	0.000
Variances				
CONTACTW	0.194	0.012	16.348	0.000
PREJW	0.686	0.028	24.448	0.000
Residual Variances				
CON1	0.255	0.012	22.040	0.000
CON2	0.507	0.022	23.208	0.000
CON3	0.452	0.023	19.639	0.000
PREJ1	0.299	0.020	14.631	0.000
PREJ2	0.450	0.019	23.736	0.000
PREJ3	0.333	0.018	18.455	0.000
Between-level !Results for the measurement models on Level 2 follow				
CONTACTB BY				
CON1	1.000	0.000	999.000	999.000
CON2	1.441	0.051	28.219	0.000
CON3	1.540	0.056	27.506	0.000
PREJB BY				
PREJ1	1.000	0.000	999.000	999.000
PREJ2	0.740	0.023	32.135	0.000
PREJ3	0.896	0.024	37.300	0.000
PREJB WITH				
CONTACTB	-0.064	0.008	-8.522	0.000

Intercepts				
CON1	1.792	0.019	93.465	0.000
CON2	2.067	0.028	72.847	0.000
CON3	2.600	0.026	98.579	0.000
PREJ1	2.529	0.024	103.729	0.000
PREJ2	2.061	0.020	100.898	0.000
PREJ3	2.302	0.024	97.336	0.000
Variances				
CONTACTB	0.059	0.007	8.434	0.000
PREJB	0.073	0.012	5.902	0.000
Residual Variances				
CON1	0.003	0.003	0.847	0.397
CON2	0.023	0.009	2.528	0.011
CON3	0.001	0.006	0.249	0.803
PREJ1	0.017	0.006	2.963	0.003
PREJ2	0.000	0.005	0.079	0.937
PREJ3	0.005	0.006	0.827	0.408

## Example 2

### Mplus code (Mplus input file) and excerpts from the Mplus output for example 2

```

Title:      Level 2 Outcome

DATA:      FILE IS example2.dat; !text file containing raw data in wide format

VARIABLE:  NAMES ARE district I C T VP AV;
           MISSING ARE ALL (-99); !missing data denoted "9" oder "-99" in example2.dat
           CLUSTER IS district; !Level 2 group identifier
           BETWEEN IS I AV; !identify variables with only Between variance
                        !variables that are not defined as "BETWEEN IS" or "WITHIN IS"
                        !can have both Within and Between variance

ANALYSIS:  TYPE IS TWOLEVEL; !tell Mplus to perform multilevel modeling
           MCONVERGENCE IS 0.001;

MODEL:     !model specification follows (see Figure 2)
           %WITHIN% !Model for Within effects follows
           VP ON T C;
           T ON C;

           %BETWEEN% !Model for Between effects follows
           C T ON I;
           T ON C;
           VP ON T C;
           AV ON VP;

!Model part for requesting significance tests for the indirect effects
MODEL INDIRECT:
  AV IND I; !all indirect effects for I on AV (ending in AV and starting in I)
  AV IND C; !all indirect effects for C on AV (ending in AV and starting in C)

!Note. I = % of stigmatized immigrants; C = positive contact with stigmatized immigrants;
!T = perceived threat; VP = SVP voting propensity; AV = actual SVP vote

```

### Excerpts from the Output

#### MODEL RESULTS

		Estimate	S.E.	Est./S.E.	Two-Tailed P-Value
Within-level !Results on the within-level					
VP	ON				
	T	1.388	0.083	16.814	0.000
	C	-0.170	0.035	-4.900	0.000
T	ON				
	C	-0.156	0.010	-15.708	0.000
Variances					
	C	7.302	0.335	21.806	0.000
Residual Variances					



T	1.032	0.030	34.220	0.000
VP	9.000	0.351	25.631	0.000

Between-level !Results on the between-level

C	ON				
I		-0.029	0.024	-1.171	0.241
T	ON				
I		0.034	0.014	2.372	0.018
C		-0.387	0.034	-11.247	0.000
VP	ON				
T		2.426	0.167	14.511	0.000
C		-1.185	0.118	-10.087	0.000
AV	ON				
VP		9.054	1.226	7.388	0.000
Intercepts					
AV		-1.700	4.257	-0.399	0.690
C		0.957	0.132	7.261	0.000
T		3.390	0.075	45.298	0.000
VP		-3.402	0.629	-5.412	0.000
Residual Variances					
AV		17.703	15.903	1.113	0.266
C		0.131	0.009	14.776	0.000
T		0.032	0.006	5.626	0.000
VP		0.000	0.000	4.614	0.000

!Results for indirect effects follow

TOTAL, TOTAL INDIRECT, SPECIFIC INDIRECT, AND DIRECT EFFECTS

	Estimate	S.E.	Est./S.E.	Two-Tailed P-Value
--	----------	------	-----------	-----------------------

WITHIN

BETWEEN !Total indirect and specific indirect effects on the between-level

Effects from I to AV

Total	1.293	0.289	4.474	0.000
Total indirect	1.293	0.289	4.474	0.000

Specific indirect

AV				
VP				
C				
I	0.307	0.253	1.215	0.224

AV				
VP				
T				
I	0.742	0.330	2.246	0.025

AV				
VP				
T				
C				
I	0.243	0.179	1.358	0.174

Effects from C to AV

Total	-19.229	3.008	-6.392	0.000
Total indirect	-19.229	3.008	-6.392	0.000

Specific indirect

AV				
VP				
C	-10.731	1.576	-6.808	0.000

AV

VP				
T				
C	-8.498	1.874	-4.533	0.000

### Example 3

#### Mplus code (Mplus input file) and excerpts from the Mplus output for example 3

```

TITLE:      MSEM for testing complex multilevel mediation model

DATA:      FILE IS example3.dat; !text file containing raw data in wide format

VARIABLE:  NAMES ARE smpt D PD C T OT IT NT OA;
            USEVARIABLES ARE D PD C T OT IT NT OA;
            CLUSTER IS smpt; !Level 2 group identifier
            MISSING ARE ALL (-99); !missing data denoted "-99" in example3.dat
            BETWEEN IS D; !identify variables with only Between variance
                        !variables that are not defined as "BETWEEN IS" or "WITHIN IS"
                        !can have both Within and Between variance

ANALYSIS:  TYPE = TWOLEVEL; !tell Mplus to perform multilevel modeling

MODEL:     model specification follows (see Figure 3)
            %WITHIN% !Specification of the within-level model
            OT IT NT OA ON C T PD;
            C T ON PD;
            T ON C;

            %BETWEEN% !Specification of the between-level model
            OT IT NT OA ON C T D;
            C T ON D;
            T ON C;
            PD;

            MODEL INDIRECT: !Requesting significance tests for indirect effects
            OT IND PD;      !indirect effects for PD on outcomes on the within-level
            IT IND PD;
            NT IND PD;
            OA IND PD;

            OT IND D;      !indirect effects for PD on outcomes on the within-level
            IT IND D;
            NT IND D;
            OA IND D;

!Note. D = Objective diversity; PD = perceived diversity ; C = intergroup contact;
!T = threat; OT = outgroup trust; IT = ingroup trust; NT = neighbourhood trust;
!OA = outgroup attitudes

```

#### Excerpts from the Output

##### MODEL RESULTS

		Estimate	S.E.	Est./S.E.	Two-Tailed P-Value
Within-level !Results on the within-level					
OT	ON				
C		0.040	0.014	2.768	0.006
T		-0.305	0.020	-15.640	0.000
PD		-0.021	0.015	-1.398	0.162
IT	ON				
C		0.022	0.019	1.146	0.252
T		-0.176	0.025	-7.163	0.000
PD		-0.021	0.020	-1.074	0.283
NT	ON				
C		0.037	0.023	1.609	0.108
T		-0.131	0.024	-5.425	0.000
PD		-0.072	0.025	-2.878	0.004
OA	ON				

C			0.200	0.058	3.470	0.001
T			-0.834	0.074	-11.229	0.000
PD			0.043	0.059	0.718	0.473
C	ON					
PD			0.303	0.028	10.761	0.000
T	ON					
PD			0.025	0.025	1.005	0.315
C			-0.192	0.025	-7.620	0.000
IT	WITH					
OT			0.133	0.010	13.685	0.000
NT	WITH					
OT			0.071	0.012	6.088	0.000
IT			0.120	0.015	8.060	0.000
OA	WITH					
OT			0.162	0.025	6.423	0.000
IT			0.099	0.031	3.195	0.001
NT			0.023	0.037	0.622	0.534

Between-level !Results on the between-level

OT	ON					
C			0.037	0.071	0.526	0.599
T			-0.534	0.089	-6.016	0.000
D			0.404	0.099	4.095	0.000
IT	ON					
C			0.045	0.099	0.454	0.649
T			-0.494	0.136	-3.627	0.000
D			0.562	0.122	4.589	0.000
NT	ON					
C			-0.031	0.108	-0.288	0.774
T			-0.566	0.146	-3.870	0.000
D			0.605	0.144	4.192	0.000
OA	ON					
C			0.230	0.277	0.831	0.406
T			-1.313	0.421	-3.121	0.002
D			0.158	0.415	0.380	0.704
C	ON					
D			-0.835	0.138	-6.050	0.000
T	ON					
D			0.170	0.135	1.263	0.206
C			-0.291	0.122	-2.386	0.017
IT	WITH					
OT			0.027	0.007	4.002	0.000
NT	WITH					
OT			0.031	0.007	4.257	0.000
IT			0.048	0.011	4.607	0.000
OA	WITH					
OT			0.026	0.018	1.436	0.151
IT			0.017	0.025	0.701	0.483
NT			-0.002	0.027	-0.086	0.931

!Results for indirect effects follow, both on the within-level and between-level

TOTAL, TOTAL INDIRECT, SPECIFIC INDIRECT, AND DIRECT EFFECTS

	Estimate	S.E.	Est./S.E.	Two-Tailed P-Value
WITHIN				
Effects from PD to OT				
Total	0.002	0.016	0.093	0.926

Total indirect	0.022	0.009	2.404	0.016
Specific indirect				
OT				
C				
PD	0.012	0.005	2.601	0.009
OT				
T				
PD	-0.008	0.008	-1.007	0.314
OT				
T				
C				
PD	0.018	0.003	6.049	0.000
Direct				
OT				
PD	-0.021	0.015	-1.398	0.162
Effects from PD to IT				
Total	-0.009	0.019	-0.452	0.651
Total indirect	0.013	0.007	1.797	0.072
Specific indirect				
IT				
C				
PD	0.007	0.006	1.137	0.255
IT				
T				
PD	-0.004	0.004	-0.994	0.320
IT				
T				
C				
PD	0.010	0.002	5.079	0.000
Direct				
IT				
PD	-0.021	0.020	-1.074	0.283
Effects from PD to NT				
Total	-0.056	0.024	-2.313	0.021
Total indirect	0.016	0.008	2.089	0.037
Specific indirect				
NT				
C				
PD	0.011	0.007	1.608	0.108
NT				
T				
PD	-0.003	0.003	-0.979	0.328
NT				
T				
C				
PD	0.008	0.002	4.421	0.000
Direct				
NT				
PD	-0.072	0.025	-2.878	0.004
Effects from PD to OA				
Total	0.131	0.064	2.047	0.041
Total indirect	0.088	0.028	3.139	0.002
Specific indirect				

OA C PD	0.061	0.018	3.402	0.001
OA T PD	-0.021	0.021	-1.005	0.315
OA T C PD	0.048	0.009	5.579	0.000
Direct OA PD	0.043	0.059	0.718	0.473
BETWEEN				
Effects from D to OT				
Total	0.152	0.081	1.871	0.061
Total indirect	-0.252	0.080	-3.126	0.002
Specific indirect				
OT C D	-0.031	0.058	-0.536	0.592
OT T D	-0.091	0.074	-1.224	0.221
OT T C D	-0.130	0.057	-2.284	0.022
Direct OT D	0.404	0.099	4.095	0.000
Effects from PD to IT				
Total	0.000	0.000	999.000	0.000
Total indirect	0.000	0.000	999.000	0.000
Effects from D to IT				
Total	0.320	0.092	3.482	0.000
Total indirect	-0.242	0.092	-2.616	0.009
Specific indirect				
IT C D	-0.038	0.082	-0.459	0.647
IT T D	-0.084	0.072	-1.176	0.240
IT T C D	-0.120	0.058	-2.054	0.040
Direct IT D	0.562	0.122	4.589	0.000
Effects from PD to NT				

Total	0.000	0.000	999.000	0.000
Total indirect	0.000	0.000	999.000	0.000
Effects from D to NT				
Total	0.397	0.108	3.686	0.000
Total indirect	-0.207	0.112	-1.859	0.063
Specific indirect				
NT				
C				
D	0.026	0.091	0.285	0.776
NT				
T				
D	-0.096	0.080	-1.198	0.231
NT				
T				
C				
D	-0.137	0.069	-1.999	0.046
Direct				
NT				
D	0.605	0.144	4.192	0.000
Effects from PD to OA				
Total	0.000	0.000	999.000	0.000
Total indirect	0.000	0.000	999.000	0.000
Effects from D to OA				
Total	-0.576	0.287	-2.011	0.044
Total indirect	-0.734	0.290	-2.529	0.011
Specific indirect				
OA				
C				
D	-0.192	0.231	-0.831	0.406
OA				
T				
D	-0.223	0.191	-1.170	0.242
OA				
T				
C				
D	-0.319	0.166	-1.918	0.055
Direct				
OA				
D	0.158	0.415	0.380	0.704