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# Modeling contextual effects using individual-level data and without aggregation: an illustration of multilevel factor analysis (MLFA) with collective efficacy

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## Abstract

Population health scientists increasingly study how contextual-level attributes affect individual health. A major challenge in this domain relates to measurement, i.e., how best to measure and create variables that capture characteristics of individuals and their embedded contexts. This paper presents an illustration of multilevel factor analysis (MLFA), an analytic method that enables researchers to model contextual effects using individual-level data without using derived variables. MLFA uses the shared variance in sets of observed items among individuals within the same context to estimate a measurement model for latent constructs; it does this by decomposing the total sample variance-covariance matrix into *within*-group (e.g., individual-level) and *between*-group (e.g., contextual-level) matrices and simultaneously modeling *distinct* latent factor structures at each level. We illustrate the MLFA method using items capturing collective efficacy, which were self-reported by 2,599 adults in 65 census tracts from the Los Angeles Family and Neighborhood Survey (LAFANS). MLFA identified two latent factors at the individual level and one factor at the neighborhood level. Indicators of collective efficacy performed differently at each level. The ability of MLFA to identify different latent factor structures at each level underscores the utility of this analytic tool to model and identify attributes of contexts relevant to health.

**Keywords:** Multilevel, Factor analysis, Environment, Ecological, Context, Latent variable, Collective efficacy, Neighborhood

Population health scientists are increasingly interested in studying multilevel phenomena, or how features of the social and physical contexts in which individuals live, learn, work, and play (e.g., neighborhoods, schools, or workplaces) are associated with individual health, disease, and behavior [1,2]. A major challenge faced by multilevel researchers relates to measurement and how best to measure features of contexts and create variables that capture both the characteristics of individuals and the contexts in which they are embedded. Identifying novel measures to capture the features of contexts that may be relevant to health is an area where multilevel researchers have urged for more progress [3-8].

One of the best examples of the challenges related to and limitations of existing approaches with regards to measurement of multilevel phenomena is evident in research on collective efficacy. Collective efficacy was first articulated in a paper by Sampson and colleagues as a feature of neighborhoods that consists of two dimensions: social cohesion among neighbors (social cohesion) and neighbors' willingness to intervene on behalf of the common good (informal social control) [9]. Since its introduction, collective efficacy has been one of the most heavily studied constructs in epidemiological and population-based research, particularly neighborhood studies, with more than 5,000 articles citing the paper introducing the concept. Collective efficacy has been found in numerous empirical studies to be positively associated with many health and developmental outcomes [9-14].

As shown in Table 1, several approaches have been used to create variables that capture collective efficacy

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**Table 1 Approaches used to construct variables to model the effects of collective efficacy or related social-environmental variables, such as income inequality or social capital**

Variable approach	Description	Examples
<i>Derived variable</i>		
Based on group-level mean	Derived variables are created by summarizing the characteristics of individuals within a group, using means, medians, proportions, or measures of dispersion (e.g., variances) or other aggregation approaches	
	Use average individual responses to items on a given scale; these means are then subsequently averaged across individuals living in the same context (e.g., neighborhood) to arrive at a contextual-level measure.	[10,14,16,17]
Based on group-level variance	Use average individual responses to items on a given scale; the variance (or standard deviation) in these means are then examined among individuals living in the same context (e.g., neighborhood) to arrive at a contextual-level measure.	[19]
<i>Factor Analysis</i>		
Single-level factor analysis	Capture the shared variance among an observed set of variables in terms of a potentially smaller number of unobserved constructs or latent factors.	
	Latent factors are estimated at only one level (i.e., the individual or contextual level).	[18]
Multilevel factor analysis (MLFA)	Latent factors are estimated at two-levels of analysis. Latent factors structures can differ at each level of analysis.	[24-28]
<i>Hierarchical Latent Variable Model</i>		
	A special case of the 2-level MLFA that imposes stricter parameter constraints than the most general MLFA wherein latent factors are estimated at only the individual level with the factor variances decomposed into within- and between-group components.	[9,51]

or related contextual-level social phenomena, such as income inequality or social capital. The most popular approach has been to create a derived variable, which entails summarizing the characteristics of individuals within a group, using means, medians, proportions, or measures of dispersion (e.g., variances) or other aggregation approaches [15]. Means have been the most popular type of derived variable used in research on collective efficacy as well as other areas of multilevel research. To construct these group or contextual-level means, the major strategy has been to first average individual responses to items on a given scale; these means are then subsequently averaged across individuals living in the same context (e.g., neighborhood) to arrive at a contextual-level measure [10,14,16-19].

A second approach has been to use factor analytic or latent variable models to determine whether multiple items should be grouped together in a common construct. Although factor analytic methods can be conducted at one or more levels of analysis (e.g., individual level, contextual level, or both), the majority of studies have focused on single-level factor analytic approaches [18]. Few studies have used latent variable approaches to study collective efficacy, even though the authors introducing the concept used a hierarchical linear latent variable modeling approach to study collective efficacy and estimate its relationship to violent crime [9].

While both derived variables and single-level factor analytic approaches are widely used and easy to construct,

their use in multilevel research may be problematic in some cases. For example, there may be instances when more than one variable best represents the contextual-level phenomenon. Moreover, there may also be instances when it is misleading to assume the function of the items and how they relate to each other is the same at all levels of analysis. New approaches are therefore needed that allow researchers to model contextual effects using individual-level data when existing measurement strategies (e.g., derived variables, single-level factor analyses) are not ideal.

In an effort to expand the population health scientist's toolkit, this paper provides an applied example of one analytic technique – multilevel factor analysis (MLFA) – that is a good alternative to existing approaches to create group or contextual-level measures. MLFA is not a new method, as it was first articulated more than 25 years ago [20-23]. However, the method has not yet been widely used, especially in population health and epidemiology. MLFA allows researchers to both model contextual effects using individual-level data without using derived variables and create variables that capture individual as well as group-level variability using one or more measures at each level of analysis (see for example [24-28]).

MLFA is part of a family of factor analytic models that seek to capture the shared variance among an observed set of variables in terms of a potentially smaller number of unobserved constructs or latent factors. Conceptually

and analytically, MLFA is distinct from the other measurement approaches, including derived variables, single-level factor analyses, and hierarchical latent variable models (HLVM), which all assume the constructs of interest are the *same* at each level of analysis. Single-level exploratory (EFA) or confirmatory factor analysis (CFA) estimates latent factors at only one level (i.e., the individual or contextual level). HLVM also estimates latent factors at only one level but captures both within- and between-level variability in those factors. In contrast, MLFA allows for different latent factor structures at each level of analysis. This occurs because the MLFA decomposes the total sample variance-covariance matrix into *within*-group (i.e., individual-level, within a context) and *between*-group (i.e., contextual-level) matrices and simultaneously models *distinct* latent factor structures at each of these levels [22,29,30]. As we detail below, HLVM is a special case of MLFA. Thus, MLFA can be viewed as an analytic approach that allows the user to relax some of the potentially untenable assumptions and constraints imposed by the HLVM specification.

In this methodological demonstration, we apply MLFA to examine the underlying factor structure of items measuring collective efficacy and compare the results to the closest analytic alternative, the HLVM. Although our focus is on collective efficacy for demonstration purposes, the MLFA technique can be applied to numerous other possible contextual-level social constructs. The MLFA technique could also be extended to evaluate the measurement quality (e.g., reliability and validity) of contextual or ecological measures, including those that are directly assessed (rather than ascertained through data collected on individuals), as has been advocated by researchers concerned with “ecometrics” [6,31].

A web-based Technical Guide (see Additional file 1) is provided to guide users in implementing MLFA in MPlus. This Technical Guide is intended to guide readers on the procedures to fit and interpret results from two multilevel factor analytic models: (1) a multilevel exploratory factor analysis (ML-EFA), and (2) multilevel confirmatory factor analysis (ML-CFA).

## Methods

### Sample and study design

Data came from the Los Angeles Family and Neighborhood Survey (L.A. FANS), a longitudinal study examining the impact of neighborhoods on children’s development and well-being [32]. The study followed a stratified random sample of 3,090 households from 65 census tracts in Los Angeles County. Within each household that contained both adults and school-aged children, a randomly selected adult (RSA) was chosen, who completed surveys at Wave

I (Spring 2000–Fall 2001). For the current study, we used data on perceptions of the neighborhood collected from the RSA. Our analytic sample consisted of 2,594 RSA respondents living in 65 census tracts. Respondents were primarily female (69.1%), Latino(a) (59.5%), and non-home owners (59.4%), with a mean age of 38.8 years (sd = 13.6).

### Measures

#### Collective efficacy

Based on previous work [9], collective efficacy was measured using 10 items that captured both perceived neighborhood informal social control and social cohesion [10].

Social cohesion was measured using seven items (refer to items 1–7 in Table 2) rated on a five-point scale (1 = strongly agree to 5 = strongly disagree). Informal social control was measured using three items (refer to items 8–10 in Table 2) rated on a five-point scale (1 = very unlikely to 5 = very likely) indicating how likely the respondent would be to intervene if they witnessed these three events.

#### Statistical analysis

We used multilevel factor analysis (MLFA), a method that models the responses for person  $i$  in cluster  $j$  (e.g., neighborhood) to a set of  $M$  items (or indicator variables), denoted  $\mathbf{y}_{ij} = (y_{1ij}, \dots, y_{Mij})$ , as a function of both individual-level (i.e., *within*-group or “Level 1”) and neighborhood-level (i.e., *between*-group or “Level 2”) factors, represented by  $\boldsymbol{\eta}_W$  and  $\boldsymbol{\eta}_B$ , respectively.

The within-group model is given by

$$\mathbf{y}_{ij} = \mathbf{v}_j + \boldsymbol{\Lambda}_W \boldsymbol{\eta}_{Wij} + \boldsymbol{\epsilon}_{ij}, \tag{1}$$

where  $\mathbf{v}_j$  is a vector of the neighborhood  $j$ ’s mean responses for each of the  $M$  items for the population of individuals embedded in neighborhood  $j$ ;  $\boldsymbol{\eta}_{Wij}$  is a vector of individual  $i$ ’s values for the individual-level factors, with  $E(\boldsymbol{\eta}_W) = \mathbf{0}$  and  $\text{Var}(\boldsymbol{\eta}_W) = \boldsymbol{\Psi}_W$ ;  $\boldsymbol{\Lambda}_W$  is a matrix of factor loadings describing the relationships between the individual-level factors,  $\boldsymbol{\eta}_W$ , and the indicator variables,  $\mathbf{y}_{ij}$ ; and  $\boldsymbol{\epsilon}_{ij}$  is the residual for individual  $i$  in neighborhood  $j$ , with  $E(\boldsymbol{\epsilon}) = \mathbf{0}$  and  $\text{Var}(\boldsymbol{\epsilon}) = \boldsymbol{\theta}$ . Typically, with continuous  $y$ s, the residuals and factors are specified to be normally distributed, with all residuals uncorrelated with each other and with the factors.

The between-group model is given by

$$\mathbf{v}_j = \boldsymbol{\gamma} + \boldsymbol{\Lambda}_B \boldsymbol{\eta}_{Bj} + \boldsymbol{\zeta}_j, \tag{2}$$

where  $\boldsymbol{\gamma}$  is a vector of overall means for the  $M$  items;  $\boldsymbol{\eta}_{Bj}$  is a vector of neighborhood  $j$ ’s values for the group-level factors, with  $E(\boldsymbol{\eta}_B) = \mathbf{0}$  and  $\text{Var}(\boldsymbol{\eta}_B) = \boldsymbol{\Psi}_B$ ;  $\boldsymbol{\Lambda}_B$  is a

**Table 2 Intraclass Correlation Coefficients (ICC) for indicator variables in the Los Angeles Family and Neighborhood Study (LAFANS) n = 2594**

Indicator variables	Intraclass correlation coefficient		
	Total sample N = 2594	Sample one n = 1291	Sample two n = 1303
1...this is a close-knit neighborhood	0.083	0.112	0.121
2...there are adults that kids look up to	0.198	0.253	0.216
3...people around here are willing to help their neighbors	0.133	0.142	0.174
4...people in this neighborhood generally don't get along with each other	0.149	0.148	0.178
5...adults watch out that kids are safe	0.085	0.112	0.089
6...people in this neighborhood do not share the same values	0.120	0.174	0.114
7...people in this neighborhood can be trusted	0.203	0.198	0.254
8...children were skipping school and hanging out on a street corner	0.104	0.131	0.125
9...children were spray-painting graffiti on a local building	0.262	0.299	0.273
10...children were showing disrespect to an adult	0.062	0.093	0.090

ICC refers to the proportion of variance in the indicator variable that is due to differences across neighborhoods. Neighborhoods were defined here as census tracts.

Items number 4 and 6 were reverse coded.

matrix of factor loadings describing the relationships between the group-level factors,  $\eta_B$ , and the group-level random intercept indicators,  $v_j$ ; and  $\zeta_j$  is the residual for neighborhood  $j$ , with  $E(\zeta) = \mathbf{0}$  and  $\text{Var}(\zeta) = \sigma$ . Like the within-group model, the residuals and factors are specified to be normally distributed, with all residuals uncorrelated with each other and with the factors.

Substituting Equation 2 into Equation 1 yields a single combined model:

$$y_{ij} = \gamma + \Lambda_w \eta_{wij} + \Lambda_B \eta_{Bj} + \zeta_j + \epsilon_{ij}, \tag{3}$$

showing that the observed responses at the individual level are specified as distinct effects of both individual- and group-level factors. These effects are depicted in Figure 1 by a path diagram for a hypothetical six-item MLFA with two within-group and one between-group factors. The variables (observed in squares and latent in circles) within the “Individual  $i$ ” box are variables that vary across each individual embedded in neighborhood  $j$ . The variables outside the “Individual  $i$ ” box and within the “Neighborhood  $j$ ” box vary across each neighborhood, but are constant for all individuals within a given neighborhood. The individual-level and neighborhood-level residuals are represented by the small arrows pointing to the observed  $y$ s and the neighborhood-level random intercept, respectively.

The model described in Equations 1 and 2 can be extended to non-continuous (e.g., binary, ordinal, count, etc.) indicator variables using a generalized linear model formulation. Briefly (and as outlined in greater detail in [33,34]), any vector of indicator variables,  $y_{ij}$ , can be

expressed as the sum of the individual expected values,  $\mu_{ij}$  and the individual residuals,  $\epsilon_{ij}$ ; that is,

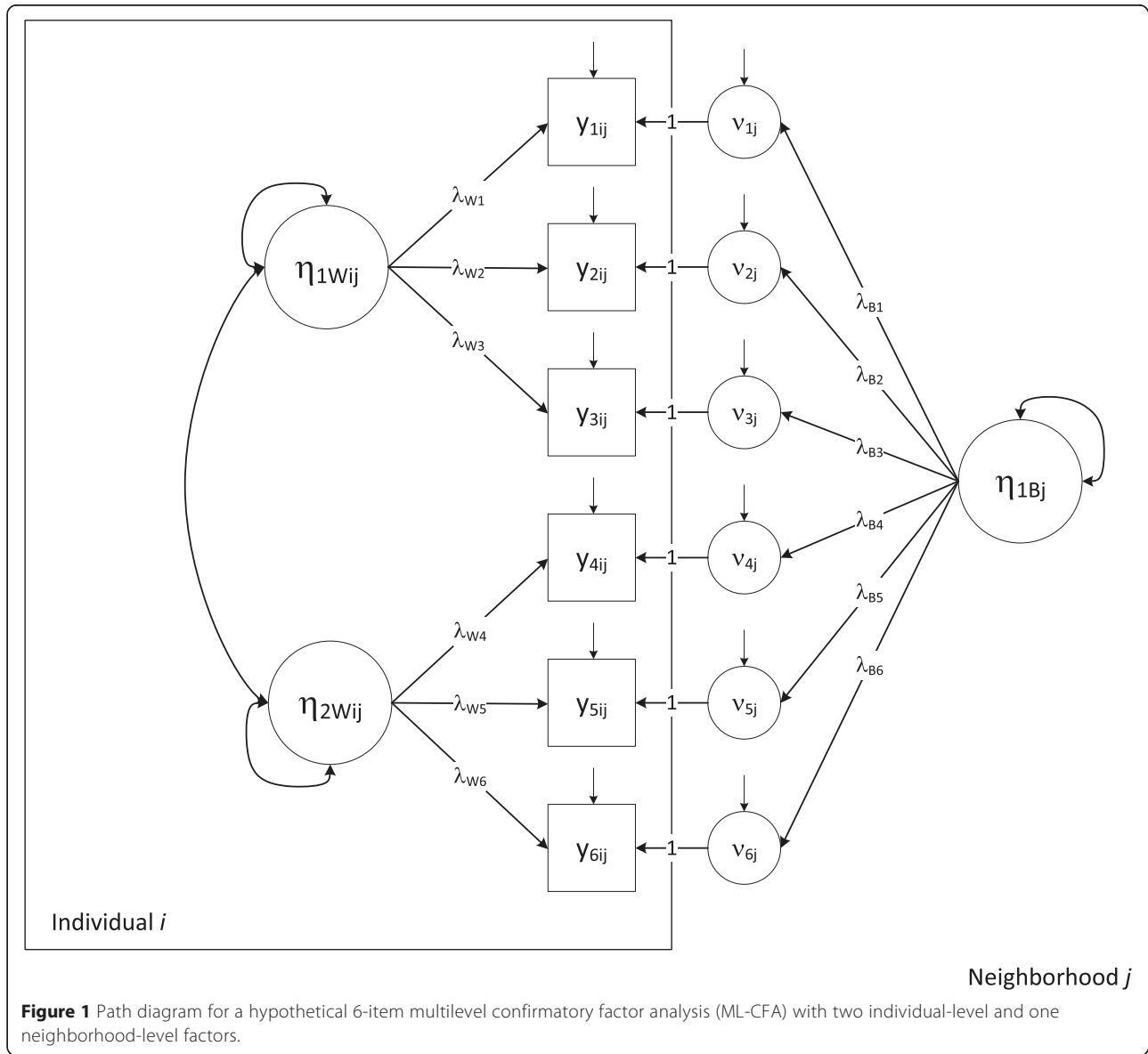
$$y_{ij} = \mu_{y_{ij}} + \epsilon_{ij}. \tag{4}$$

The distribution of the residuals is chosen to correspond to the measurement scale of the observed indicators, e.g., a Bernoulli distribution for binary indicators. A link function,  $g$ , then relates the individual expected values to a linear combination of the latent factors; that is,

$$g(\mu_{y_{ij}}) = v_j + \Lambda_w \eta_{wij}. \tag{5}$$

The between-group model remains the same. In the case of continuous approximately normally distributed observed outcomes, the usual specification is the identity link function, resulting in straightforward linear regressions relating the observed variables to the latent factor. In the case of binary indicators, one might choose a logit link function, resulting in logistic regressions relating the observed categorical indicators to the latent factors. In the case of an observed ordinal response scale, as with our indicators of collective efficacy, we used the ordinal probit link function [35]. All models were estimated via weighted least squares using a diagonal weight matrix with standard errors and mean- and variance-adjusted chi-square test statistics that used a full weight matrix (WLSMV).

To showcase the MLFA approach, we conducted our analyses in four steps. First, we calculated intraclass correlation coefficients (ICCs) for each item. These ICCs



provide information about the proportion of variance in each item that is due to differences between neighborhoods. Second, we used polychoric correlations (where each correlation is a measure of the pairwise association for two ordinal variables, which rests upon the assumption of an underlying joint continuous distribution) to examine the strength, direction, and magnitude of the associations among the items. We examined these associations in two correlation matrices: (1) the within-level (individual) matrix; and (2) the between-level (neighborhood) matrix. Third, we randomly split the sample into two equally sized subsamples and conducted a multilevel exploratory analysis (ML-EFA) with one subsample and a confirmatory analysis (ML-CFA) with the other. An EFA is ideal to use in situations when researchers lack

hypotheses concerning the number of latent factors underlying an item set or what the relationships are between each factor and the items; a CFA is more appropriate when researchers have hypotheses regarding the number of factors and the factor-item relationships or are seeking to test the validity of a theoretical model [36,37]. Both techniques are shown here for illustration purposes.

Finally, we fit the hierarchical latent variable model (HLVM) outlined by Sampson et al. [9] as a comparison. The HLVM is a special case of the MLFA, where the factor measurement model is the same (i.e., same number of factors, same loading patterns, and same loading values) at the within- and between-group models and there is no between-group item-specific residual. HLMV

can also be seen as an extension of a single-level factor analysis, where the overall factor variance-covariance structure is comprised of within- and between-group variance-covariance components. The important distinction between the MLFA and HLVM is that the factors in the HLVM are only defined at the within-level while in the MLFA there are *distinct* factors defined at *both* the within- and between-level models. For the HLVM, the within-group is the same as for the MLFA, as given in Equation (1). The between-group model is given by

$$\mathbf{v}_j = \boldsymbol{\gamma} + \boldsymbol{\Lambda}_W \boldsymbol{\eta}_{Bj}. \tag{6}$$

Substituting Equation (6) into Equation (1) yields a single combined model for the HLVM:

$$\mathbf{y}_{ij} = \boldsymbol{\gamma} + \boldsymbol{\Lambda}_W (\boldsymbol{\eta}_{Wij} + \boldsymbol{\eta}_{Bj}) + \boldsymbol{\epsilon}_{ij}, \tag{7}$$

where  $\boldsymbol{\gamma}$  is a vector of overall means for the  $M$  items;  $\boldsymbol{\eta}_{Wij}$  and  $\boldsymbol{\eta}_{Bj}$  capture within-group across-person variability and between-group variability, respectively, in a set of latent factors,  $\boldsymbol{\eta}$ , with  $E(\boldsymbol{\eta}) = \mathbf{0}$  and  $\text{Var}(\boldsymbol{\eta}) = \boldsymbol{\Psi}_W + \boldsymbol{\Psi}_B$ ;  $\boldsymbol{\Lambda}_W$  is a matrix of factor loadings describing the relationships between the factors,  $\boldsymbol{\eta}$ , and the indicator variables,  $\mathbf{y}_{ij}$ ; and  $\boldsymbol{\epsilon}_{ij}$  is the residual for individual  $i$  in neighborhood  $j$ , with  $E(\boldsymbol{\epsilon}) = \mathbf{0}$  and  $\text{Var}(\boldsymbol{\epsilon}) = \boldsymbol{\theta}$ . The HLVM can be more simply written as

$$\begin{aligned} \mathbf{y}_{ij} &= \boldsymbol{\gamma} + \boldsymbol{\Lambda} \boldsymbol{\eta}_{ij} + \boldsymbol{\epsilon}_{ij}, \\ \boldsymbol{\eta}_{ij} &= \boldsymbol{\alpha}_j + \boldsymbol{\xi}_{ij}, \end{aligned} \tag{8}$$

showing that the observed indicators are a function of only individual-level factors with the variance-covariance of those factors explicitly decomposed by the model into within-group and between-group variance components. As with the MLFA, the HLVM can use a generalized linear model approach to specify the relationships between the items and the factor in the case of non-continuous item responses. The specific HLVM model used by Sampson et al. [9], expressed as a three-level model with items nested within persons nested within clusters, imposes the additional constraints of all factor loadings being fixed at one and all item residual variances constrained to be equal.

We conducted all analyses using Mplus software version 7. Mplus handles missing data under the missing at random assumption (MAR) using the WLSMV estimator, which allows missingness to be a function of the observed covariates, but not observed outcomes, as is the case for full information maximum likelihood (FIML). When there are no covariates in the model, as is the case here, this is analogous to pairwise present analysis [38,39]. Analyses also included sampling weights to adjust for non-response and the unequal probability of

selection of neighborhoods and households into the sample. Across all models, we evaluated goodness-of-fit using the model chi-square test, normed comparative fit index (CFI; [40]), root mean square error of approximation (RMSEA; [41]), and the standardized root mean square residual (SRMR; [38]). These statistics provide information about how well the model-estimated population correlations reproduce the sample correlations. Acceptable model fit was determined by a non-significant chi-square test, CFI values greater than 0.95, and RMSEA and SRMR values below 0.10 [42]. The CFI, RMSEA, and SRMR values were given more emphasis than the chi-square test, as the chi-square test statistic is often significant (implying there is significant misfit of the model to the data) when the sample size is large. In the MLFA, an SRMR is provided at both the within and between level. As there are no established guidelines for interpreting the SRMR at the between level, we considered the guidelines that are typically applied for single-level analyses ( $\leq 0.10$ ). We also examined the residuals for the between-level correlation matrix, which are an indicator of model fit.

Of note, there are alternative statistical software packages, such as MLwiN or MLwiN via Stata, that can be used to estimate MLFA models. Readers interested in fitting the MLFA using MLwiN are referred to the MLwiN website: <http://www.bristol.ac.uk/cmm/software/mlwin/>. In addition, the MLFA method can also be fit using Markov chain Monte Carlo (MCMC) methods. Such Bayesian estimation procedures may provide a particularly good alternative to maximum likelihood methods in instances when maximum likelihood is too computationally intensive or when there are some instances of a small number of individuals per cluster or when there are a small number of overall clusters [21].

## Results

### Intraclass correlation coefficients (ICC)

ICC estimates ranged from small to large in magnitude and were generally equivalent across our split samples (Table 2). In the total sample, the largest estimated ICC (0.262) was for the item “children were spray-painting graffiti on a local building.” The lowest ICC in the total sample (0.062) was for “children were showing disrespect to an adult.” Thus, most of the variability in these items was due to differences across individuals *within* rather than *between* neighborhoods. However, there was considerable variability among the indicators as to the proportion of variation explained between neighborhoods. This suggests that neighborhood-level variation is not uniform across indicators and that for some indicators, neighborhood-level influences may be more important.

**Correlations**

As shown in Tables 3 and 4, the within level (individual) and between level (neighborhood) had different correlation structures. While the average absolute correlation value at the within level was 0.304 (range  $r = 0.093$  to  $r = 0.557$ ), the average absolute correlation value at the between level was higher (average = 0.685; range  $r = 0.205$  to  $r = 0.934$ ). Some items also had markedly differently correlations at each level. For example, the items “people here do not get along with each other” and “people would intervene if children were spray painting graffiti” had a very strong correlation at the between-level ( $r = 0.858$ ), but a weak correlation at the within-level ( $r = 0.239$ ). These finding suggest the item-to-item relationships differ across the two levels of analysis (within- and between-level).

**Multilevel factor analysis (MLFA) results**

**Multilevel exploratory factor analysis (ML-EFA)**

The final ML-EFA model, which was selected based on good model-data consistency, parsimony, and interpretability, had two within-level factors and one between-level factor (Table 5). In this factor solution, the largest factor loadings for each item at the within level (0.418 to 0.773) and between level (0.462 to 0.972) ranged from moderate to high. In addition to good overall model fit, as evidenced by the CFI of 0.947 and RMSEA of 0.059, this solution also had excellent model fit specifically at the within and between levels, as shown in the SRMR values at each level 0.039 and 0.068, respectively. In contrast, the next best fitting model – the two factor within and two-factor between model – had a good overall fit ( $SRMR_{within} = 0.039$ ;  $SRMR_{between} = 0.045$ ). However, the second between-level factor had only one significantly

loading item (refer to page 21 of the online Technical Guide).

Beyond its empirical fit, the ML-EFA solution was also aligned with prior theory. At the within level, the first factor mapped on to the construct social cohesion and the second factor mapped on to the construct informal social control, as described by others [9,10]. At the between level, the indicator variables only supported one overarching factor, which has previously been labeled as collective efficacy [9,10]. Interestingly, the sixth item (people in this neighborhood do not share the same values) did not load significantly on either factor at the within level, but had a significant factor loading at the between level. This finding illustrates that indicator variables can perform differently at each level of analysis and therefore items should only be removed from a MLFA if they are determined not to function at both levels of analysis.

The first and second within-level factors were moderately correlated ( $r = 0.521$ ). The communalities, or item-specific  $R^2$  values, which refer to the proportion of an indicator’s total variance accounted for by the factor solution, ranged at the within level from a low of 8.4% (for respondents’ rating of people in the neighborhood sharing the same values) to a high of 57.1% (for respondents’ rating of people’s willingness to help neighbors) at the within level. At the between level, the communalities were higher across the items, ranging from a low of 21.4% (for neighborhoods’ collective tendency to intervene if children show disrespect to an adult) to a high of 94.4% (for neighborhoods’ collective tendency to watch out that kids are safe).

**Multilevel confirmatory factor analysis (ML-CFA)**

The ML-EFA results from the first subsample were cross-validated using ML-CFA for the second subsample.

**Table 3 Correlations among indicators at the within-level**

		1	2	3	4	5	6	7	8	9	10
1	CLOSEKNIT	1.000									
2	ADULTS	0.461	1.000								
3	HELP	0.483	0.467	1.000							
4	ALONG	0.210	0.310	0.368	1.000						
5	SAFE	0.395	0.377	0.458	0.240	1.000					
6	VALUES	0.153	0.093	0.165	0.321	0.141	1.000				
7	TRUST	0.408	0.422	0.528	0.309	0.487	0.234	1.000			
8	SKIP	0.256	0.207	0.296	0.174	0.333	0.124	0.358	1.000		
9	GRAFFITI	0.219	0.239	0.283	0.212	0.358	0.163	0.294	0.557	1.000	
10	DISRESPECT	0.287	0.202	0.285	0.194	0.261	0.125	0.278	0.470	0.476	1.000

CLOSEKNIT = this is a close-knit neighborhood; ADULTS = there are adults that kids look up to; HELP = people here are willing to help their neighbors; ALONG = people here don’t get along with each other; SAFE = adults watch out that kids are safe; VALUES = people here do not share the same values; TRUST = people in this neighborhood can be trusted; SKIP = people would intervene if children were skipping school and hanging out on the corner; GRAFFITI = people would intervene if children were spray-painting graffiti; DISRESPECT = people would intervene if children were showing disrespect to an adult. Items 4 and 6 were reverse coded. These correlations were taken from the sample used for the multilevel exploratory factor analysis (ML-EFA).

**Table 4 Correlations among indicators at the between-level**

		1	2	3	4	5	6	7	8	9	10
1	CLOSEKNIT	1.000									
2	ADULTS	0.735	1.000								
3	HELP	0.773	0.862	1.000							
4	ALONG	0.593	0.758	0.855	1.000						
5	SAFE	0.749	0.853	0.897	0.902	1.000					
6	VALUES	0.561	0.620	0.668	0.754	0.705	1.000				
7	TRUST	0.742	0.842	0.870	0.834	0.934	0.653	1.000			
8	SKIP	0.826	0.641	0.731	0.677	0.765	0.650	0.697	1.000		
9	GRAFFITI	0.729	0.858	0.870	0.857	0.865	0.725	0.823	0.757	1.000	
10	DISRESPECT	0.489	0.205	0.478	0.316	0.254	0.257	0.320	0.480	0.382	1.000

CLOSEKNIT = this is a close-knit neighborhood; ADULTS = there are adults that kids look up to; HELP = people here are willing to help their neighbors; ALONG = people here don't get along with each other; SAFE = adults watch out that kids are safe; VALUES = people here do not share the same values; TRUST = people in this neighborhood can be trusted; SKIP = people would intervene if children were skipping school and hanging out on the corner; GRAFFITI = people would intervene if children were spray-painting graffiti; DISRESPECT = people would intervene if children were showing disrespect to an adult. Items 4 and 6 were reverse coded. These correlations were taken from the sample used for the multilevel exploratory factor analysis (ML-EFA).

As shown in Table 6, the fit of the ML-CFA model was good (CFI = 0.903; RMSEA = 0.079; SRMR<sub>within</sub> = 0.054; SRMR<sub>between</sub> = 0.073). By and large, factor loadings in the ML-CFA were similar to the ML-EFA.

We also ran an alternative ML-CFA specification with the constraints imposed by the Sampson et al. version of the HLVM described earlier. The overall fit of this model was markedly worse than the ML-CFA without these restrictions ( $\chi^2 = 1445.265$ ;  $df = 86$ ;  $p\text{-value} < 0.001$ ; RMSEA = 0.110; CFI = 0.766; SRMR<sub>within</sub> = 0.095; SRMR<sub>between</sub> = 0.325), suggesting that a more restricted model lacked the model-data consistency observed with the less restrictive ML-CFA. Of note, a single-level factor analysis, which is the equivalent of adding to the HLVM a further constraint of zero between-level factor variance, would have a poorer fit than the HLVM. Although not the case here, it is possible that for another

dataset, the HLVM specification could fit equivalent to the MLFA. Such a finding would suggest that the data do not support a different factor structure at the within and between-group levels, and the HLVM could be favored as a more parsimonious model. A researcher, however, would not be able to make this determination without comparing the HLVM to the MLFA.

**Discussion**

This methodological demonstration of MLFA to collective efficacy shows that use of either simple aggregation methods, in the form of derived variables, or single-level factor analyses, may not be the best way to construct contextual-level variables from individual-level data. We arrived at this conclusion based on three sets of results. First, we found that ICC values were not the same for every item; some items showed quite high neighborhood-

**Table 5 Factor loadings of indicators for the multi-level exploratory factor analysis (ML-EFA)**

	Within-level		Between-level
	Factor 1	Factor 2	Factor 1
1...this is a close-knit neighborhood	<b>0.618</b>	0.030	<b>0.797</b>
2...there are adults that kids look up to	<b>0.642</b>	-0.034	<b>0.833</b>
3...people around here are willing to help their neighbors	<b>0.735</b>	0.038	<b>0.935</b>
4...people in this neighborhood generally don't get along with each other	<b>0.418</b>	-0.008	<b>0.931</b>
5...adults watch out that kids are safe	<b>0.630</b>	0.035	<b>0.972</b>
6...people in this neighborhood do not share the same values	0.297	0.015	<b>0.668</b>
7...people in this neighborhood can be trusted	<b>0.773</b>	-0.046	<b>0.924</b>
8...children were skipping school and hanging out on a street corner	0.121	<b>0.662</b>	<b>0.823</b>
9...children were spray-painting graffiti on a local building	0.001	<b>0.711</b>	<b>0.917</b>
10...children were showing disrespect to an adult	-0.010	<b>0.723</b>	<b>0.462</b>

$\chi^2 = 337.222$ ;  $df = 61$ ;  $p\text{-value} < 0.00001$ ; CFI = 0.947; RMSEA = 0.059; SRMR<sub>within</sub> = 0.039; SRMR<sub>between</sub> = 0.068. All factor loadings in an EFA are standardized. High EFA loadings appear in bold. Items 4 and 6 were reverse coded.



**Table 6 Standardized factor loadings of items for the Multi-Level Confirmatory Factor Analysis (ML-CFA)**

	Within-level		Between-level
	Factor 1	Factor 2	Factor 1
1...this is a close-knit neighborhood	0.622		0.774
2...there are adults that kids look up to	0.631		0.824
3...people around here are willing to help their neighbors	0.701		0.857
4...people in this neighborhood generally don't get along with each other	0.474		0.828
5...adults watch out that kids are safe	0.649		0.819
6...people in this neighborhood do not share the same values	0.266		0.807
7...people in this neighborhood can be trusted	0.681		0.897
8...children were skipping school and hanging out on a street corner		0.724	0.667
9...children were spray-painting graffiti on a local building		0.769	0.928
10...children were showing disrespect to an adult		0.613	0.353

$\chi^2 = 629.816$ ;  $df = 69$ ;  $p\text{-value} < 0.00001$ ;  $RMSEA = 0.079$ ;  $CFI = 0.903$ ;  $SRMR_{within} = 0.054$ ;  $SRMR_{between} = 0.073$ .  
 Items 4 and 6 were reverse coded.

level variation and others showed very little. The lack of uniformity in between-neighborhood variation across these items suggests neighborhood context may have differing levels of salience across this set of items and that not all items should be treated equally in terms of their importance to understanding neighborhoods.

Second, the correlation structure of the items was different across the individual (within) and neighborhood (between) levels. Specifically, the correlation among items was much higher at the between level than the within. Moreover, how the items related to each other also differed across levels; some items had high correlations at one level and modest correlations at the other. These findings provided an initial sign that there may be different factor structures at the two levels of analysis.

Third, when we ran the MLFA, we found that the best-fitting model was one that modeled collective efficacy as a two dimensional construct at the within level, consisting of the two latent constructs informal social control and social cohesion, and a one dimensional construct at the between level, consisting of collective efficacy. This two-factor within and one-factor between model was confirmed in the ML-CFA. Imposing an identical factor structure at both levels resulted in a worse-fitting model, particularly when we imposed a set of stricter constraints described in the original paper introducing collective efficacy [9]. While the stricter constraints may be reasonable and could be supported by the data in some cases, there may be instances, such as the case here, where the items were not all equally good indicators of collective efficacy and thus imposing equal factor loadings and equal residual variances constraints was not consistent with the observed data. We also found that the items performed differently in terms of their factor loadings at the within compared to between level. For example, the item “people in this

neighborhood do not share the same values” did not load at the within level, but loaded at the between. Taken together, the results of the current study suggest that collective efficacy, and perhaps other social constructs, can have very different meanings at each level of analysis and are perhaps most appropriately studied at the neighborhood level as one overarching construct and not divided into its two dimensions, informal social control and social cohesion, as has been done in some prior studies (see for example [13,43]).

Our study has the following limitations. The measure of collective efficacy was not identical to the original measure [9]. It is possible our results would have been different had we used a different measure of collective efficacy. The number of neighborhoods in this study ( $n = 65$ ) was also small relative to other studies. Moreover, our definition of neighborhoods was based on an administrative definition (i.e., Census tract), which may not adequately reflect meaningful geographic boundaries that represent distinct social experiences or cultures [44,45]. Though an imperfect measure to define neighborhoods, Census tracts are most commonly used in multi-level research in the United States [8].

Finally, the MLFA technique is, of course, not without its limitations. For example, it can be computationally intensive. Most software also only allow for two-level structures. In spite of these challenges, results of our analysis underscore the potential utility of MLFA and suggest that using other more easily implemented approaches, such as single-level factor analyses, may not be ideal. As we showed, the MFLA method revealed different latent factor structures at each level of analysis. Our results also demonstrated that imposing a simpler factor structure, with identical factor structures at each level, was not consistent with the data and resulted in a poorer-fitting model.

Results of this study have several important implications for measuring social environments potentially linked to health. Multilevel researchers have lamented the lack of progress in identifying novel measurement tools to characterize contextual-level constructs and as a result have called for new approaches [3-8]. Although more work is needed, results of the current study suggest that MLFA may be a promising method to construct variables from individual-level data for use in multilevel analyses. The MLFA technique allows researchers to use individual-level items to construct measures of the social context using a more flexible approach than other types of hierarchical models. The MLFA approach can also be easily applied with survey data, which remains the most common and cost effective type of data collected. Moreover by using MLFA, researchers establish the measurement model necessary for estimating a multilevel structural equation model (ML-SEM), where direct and indirect effects between latent variables, covariates, and individual items, existing at two or more levels of analysis, are examined [42,46,47]. Although still not widely used in epidemiology or population health, SEM models are an alternative to traditional techniques that can be used for exploratory or hypothesis-generating purposes [48] or to test more complex relationships between a set of variables [49,50].

In conclusion, our results suggest MLFA is a promising alternative to using derived variables and single-level factor analytic approaches. Future studies are warranted to validate the current results in relation to collective efficacy and extend the MLFA technique to other dimensions of the neighborhood environment as well as other social contexts that influence health.

## Additional file

**Additional file 1: Technical Appendix for the article: Modeling contextual effects using individual-level data and without aggregation: an illustration of multilevel factor analysis (MLFA) with collective efficacy.**

## Competing interests

The authors declare that they have no competing interests.

## Authors' contributions

ECD conceptualized the analytic plan, oversaw the analysis, interpreted results, drafted the manuscript, and approved the final version. KEM helped Dr. Dunn conceptualize the original study design, met regularly to review results, reviewed and edited the early draft of the manuscript, and approved the final version. WRJ carried out the analyses, helped with interpretation of results, edited the early manuscripts, and approved the final version. SVS worked with Dr. Dunn to conceptualize the original study design, reviewed and aided in interpreting early results, and approved the final version. All authors read and approved the final manuscript.

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## **Additional file 1**

From the Article: Modeling contextual effects using individual-level data and without aggregation: An illustration of multilevel factor analysis (MLFA) with collective efficacy

### **Introduction**

This appendix is intended to guide readers on the procedures to fit and interpret results from two multilevel factor analytic models: (1) a multilevel exploratory factor analysis (ML-EFA), and (2) multilevel confirmatory factor analysis (ML-CFA). Our illustration uses data analyzed in the paper by <BLIND FOR REVIEW> noted above. We used MPlus version 7 for all analyses (Muthen & Muthen, 1998-2012).

In our analysis, all data manipulation (e.g., recoding variables, etc.) was performed prior to importing the data into MPlus. For ease of implementation, we recommend all data manipulation occur in other programs (e.g., SAS, Stata, SPSS) outside of MPlus. Readers interested in specific data manipulation capabilities should refer to the MPlus manual (Muthen & Muthen, 2012).

It is important to note that in the interest of parsimony, we do not interpret every piece of the input statements or the output. Specifically, we only present the results of the most relevant models from the ML-EFA and ML-CFA, drastically reducing the length of the output. In addition, we assume readers will have some familiarity with MPlus and with factor analytic approaches. Readers interested in learning about factor analysis are referred elsewhere (Bartholomew, 2011; Kline, 2011).

## Multilevel Exploratory Factor Analysis (ML-EFA) Syntax

Mplus VERSION 7  
MUTHEN & MUTHEN

INPUT INSTRUCTIONS

Title:

EFA for Multi-level Factor Analysis

Data:

File is ML\_EFA\_CFA\_06\_27.dat ;

Variable:

Names are	caseid	SAMPID_N	hhid	pid	RSA_TYPE	wgtrsa
	wgtadlt	wgtpcg	closekni	adults	help	along
	safe	values	trust	AB6_8	AB6_9	CLOSEKNIO
	skip	graffiti	disrespe	AB8_1	AB8_2	AB9
	AB11_1	AB11_2	AB11_3	AB12	AB13	AB14
	tractx	sample1	ALONG_r	VALUES_r	AGE_YR	sex
	RB1	RB2_1	RB2_2	RB2_3	RB2_4	RB2_5
	RB2_6	AJ5	movsince	HA18_1	;	

Missing are . ;

USEOBSERVATIONS = sample1 == 1;

USEVARIABLES = closekni adults help along\_r

safe values\_r trust skip graffiti disrespe;

CATEGORICAL = closekni adults help along\_r

safe values\_r trust skip graffiti disrespe;

CLUSTER = tractx;

weight = WGTADLT;

Prior to importing the data into Mplus, we created a split sample, denoted by the variable "sample1". Specifically, a random 50% of individuals from each cluster were given a value of 1 on this variable and the other 50% a value of 0. The EFA was conducted on one subsample and the CFA with the other. Here we specify in the USEOBSERVATIONS command that only individuals with a value of "1" on sample1 are included.

The USEVARIABLES only includes the 10 items involved in the EFA.

All of the items are 5-point likert scales, so they need to be identified as categorical.

CLUSTER refers to the cluster variable (tractx = Census tract ID).

Analysis:

```
Type = twolevel efa 1 5 uw 1 5 ub;  
estimator=wlsmv;
```

Here we are telling Mplus to conduct a multilevel EFA with between 1 and 5 factors at both the within and between levels. Mplus will attempt to model every possible combination of factor structures (e.g., one factor within, one factor between; one factor within, two factors between, etc). The "uw" and "ub" are included to ask for unstructured models with no factors at each level. Since the data are categorical, we use the WLSMV estimator.

PLOT:

```
Type = plot2;
```

The plot2 option gives us scree plots for both the within and between levels.

OUTPUT:

```
modindices sampstat svalues;
```

MODINDICES provides information on how the model might be improved if it were to be modified in some way. SAMPSTAT provides sample descriptive statistics. The SVALUES option will output parameter estimates that can be used as start values in subsequent models.

## Multilevel Exploratory Factor Analysis (ML-EFA) Results

### SUMMARY OF ANALYSIS

Number of groups	1
Number of observations	1291
Number of dependent variables	10
Number of independent variables	0
Number of continuous latent variables	0

### Observed dependent variables

Binary and ordered categorical (ordinal)					
CLOSEKNI	ADULTS	HELP	ALONG_R	SAFE	VALUES_R
TRUST	SKIP	GRAFFITI	DISRESPE		

### Variables with special functions

Cluster variable	TRACTX
Weight variable (cluster-size scaling)	
WGTADLT	

Estimator	WLSMV
Rotation	GEOMIN
Row standardization	CORRELATION
Type of rotation	OBLIQUE
Epsilon value	Varies
Optimization Specifications for the Quasi-Newton Algorithm for Continuous Outcomes	
Maximum number of iterations	1000
Convergence criterion	0.100D-05
Optimization Specifications for the EM Algorithm	
Maximum number of iterations	500
Convergence criteria	
Loglikelihood change	0.100D-02
Relative loglikelihood change	0.100D-05
Derivative	0.100D-02
Optimization Specifications for the M step of the EM Algorithm for Categorical Latent variables	
Number of M step iterations	1
M step convergence criterion	0.100D-02
Basis for M step termination	ITERATION
Optimization Specifications for the M step of the EM Algorithm for Censored, Binary or Ordered Categorical (Ordinal), Unordered Categorical (Nominal) and Count Outcomes	
Number of M step iterations	1
M step convergence criterion	0.100D-02
Basis for M step termination	ITERATION
Maximum value for logit thresholds	10
Minimum value for logit thresholds	-10
Minimum expected cell size for chi-square	0.100D-01
Maximum number of iterations for H1	2000
Convergence criterion for H1	0.100D-03
Optimization Specifications for the Exploratory Factor Analysis Rotation Algorithm	
Number of random starts	30

```

Maximum number of iterations          10000
Derivative convergence criterion      0.100D-04
Optimization algorithm                FS
Integration Specifications
  Type                                STANDARD
  Number of integration points         7
  Dimensions of numerical integration  2
  Adaptive quadrature                 ON
Link                                  PROBIT
Cholesky                              ON

```

```

Input data file(s)
  ML_EFA_CFA_06_27.dat
Input data format  FREE

```

SUMMARY OF DATA

```

Number of clusters          65
Average cluster size       19.862

```

Estimated Intraclass Correlations for the Y Variables

Variable	Intraclass Correlation	Variable	Intraclass Correlation	Variable	Intraclass Correlation
CLOSEKNI	0.112	ADULTS	0.253	HELP	0.142
ALONG_R	0.148	SAFE	0.112	VALUES_R	0.174
TRUST	0.198	SKIP	0.131	GRAFFITI	0.299
DISRESPE	0.093				

These ICCs represent the between-level variance divided by the total variance for each item. Near-zero ICCs suggest there is minimal between-neighborhood variance on the item.

COVARIANCE COVERAGE OF DATA

```

Minimum covariance coverage value  0.100

```

UNIVARIATE PROPORTIONS AND COUNTS FOR CATEGORICAL VARIABLES

CLOSEKNI		
Category 1	0.070	90.618
Category 2	0.490	632.358
Category 3	0.067	86.594
Category 4	0.310	400.443
Category 5	0.063	80.987
ADULTS		
Category 1	0.090	116.224
Category 2	0.566	730.767
Category 3	0.103	132.685
Category 4	0.220	283.708
Category 5	0.021	27.616
HELP		
Category 1	0.108	139.454
Category 2	0.663	855.474
Category 3	0.062	79.917
Category 4	0.143	184.927
Category 5	0.024	31.229

It is useful to compare this output to frequency counts from the data file used for initial data management in Stata, SAS or SPSS.

This ensures that the variables were correctly pulled in to Mplus.



ALONG_R		
Category 1	0.086	111.102
Category 2	0.654	843.740
Category 3	0.084	107.866
Category 4	0.166	214.884
Category 5	0.010	13.409
SAFE		
Category 1	0.105	135.119
Category 2	0.638	824.239
Category 3	0.090	116.625
Category 4	0.143	184.433
Category 5	0.024	30.585
VALUES_R		
Category 1	0.028	36.595
Category 2	0.427	551.799
Category 3	0.115	148.123
Category 4	0.397	512.733
Category 5	0.032	41.750
TRUST		
Category 1	0.072	92.562
Category 2	0.597	771.164
Category 3	0.078	101.265
Category 4	0.215	277.510
Category 5	0.038	48.499
SKIP		
Category 1	0.200	258.256
Category 2	0.407	525.388
Category 3	0.059	75.551
Category 4	0.243	313.026
Category 5	0.091	117.535
GRAFFITI		
Category 1	0.385	496.057
Category 2	0.367	473.343
Category 3	0.037	47.379
Category 4	0.152	196.587
Category 5	0.059	76.389
DISRESPE		
Category 1	0.141	181.865
Category 2	0.439	566.717
Category 3	0.092	118.092
Category 4	0.230	296.802
Category 5	0.098	126.280

SAMPLE STATISTICS

ESTIMATED SAMPLE STATISTICS

MEANS/INTERCEPTS/THRESHOLDS

	CLOSEKNI	CLOSEKNI	CLOSEKNI	CLOSEKNI	ADULTS\$1
	-----	-----	-----	-----	-----
1	-1.555	0.162	0.346	1.636	-1.541

Note: Thresholds are one component that is estimated when the models include categorical indicators. In this case, the thresholds correspond to the negative cumulative probit for the ordinal response variable when all factors are zero.

MEANS/INTERCEPTS/THRESHOLDS					
	<u>ADULTS\$2</u>	<u>ADULTS\$3</u>	<u>ADULTS\$4</u>	<u>HELP\$1</u>	<u>HELP\$2</u>
1	0.461	0.818	2.341	-1.327	0.805
MEANS/INTERCEPTS/THRESHOLDS					
	<u>HELP\$3</u>	<u>HELP\$4</u>	<u>ALONG_R\$</u>	<u>ALONG_R\$</u>	<u>ALONG_R\$</u>
1	1.051	2.134	-1.467	0.714	1.025
MEANS/INTERCEPTS/THRESHOLDS					
	<u>ALONG_R\$</u>	<u>SAFE\$1</u>	<u>SAFE\$2</u>	<u>SAFE\$3</u>	<u>SAFE\$4</u>
1	2.507	-1.334	0.688	1.020	2.095
MEANS/INTERCEPTS/THRESHOLDS					
	<u>VALUES_R</u>	<u>VALUES_R</u>	<u>VALUES_R</u>	<u>VALUES_R</u>	<u>TRUST\$1</u>
1	-2.080	-0.111	0.210	2.027	-1.609
MEANS/INTERCEPTS/THRESHOLDS					
	<u>TRUST\$2</u>	<u>TRUST\$3</u>	<u>TRUST\$4</u>	<u>SKIP\$1</u>	<u>SKIP\$2</u>
1	0.491	0.754	2.016	-0.895	0.296
MEANS/INTERCEPTS/THRESHOLDS					
	<u>SKIP\$3</u>	<u>SKIP\$4</u>	<u>GRAFFITI</u>	<u>GRAFFITI</u>	<u>GRAFFITI</u>
1	0.466	1.443	-0.342	0.816	0.960
MEANS/INTERCEPTS/THRESHOLDS					
	<u>GRAFFITI</u>	<u>DISRESPE</u>	<u>DISRESPE</u>	<u>DISRESPE</u>	<u>DISRESPE</u>
1	1.847	-1.123	0.213	0.470	1.366

These values represent the sample variances and covariances across individuals, within neighborhoods. High values indicate greater levels of shared variance among the items.

WITHIN LEVEL VARIANCE/COVARIANCE

	CLOSEKNI	ADULTS	HELP	ALONG_R	SAFE
CLOSEKNI	1.000				
ADULTS	0.439	1.000			
HELP	0.523	0.465	1.000		
ALONG_R	0.202	0.272	0.319	1.000	
SAFE	0.400	0.359	0.476	0.248	1.000
VALUES_R	0.113	0.108	0.181	0.304	0.157
TRUST	0.423	0.463	0.545	0.290	0.542
SKIP	0.298	0.286	0.404	0.192	0.278
GRAFFITI	0.221	0.210	0.270	0.157	0.324
DISRESPE	0.268	0.199	0.287	0.144	0.247

WITHIN LEVEL VARIANCE/COVARIANCE

	VALUES_R	TRUST	SKIP	GRAFFITI	DISRESPE
VALUES_R	1.000				
TRUST	0.242	1.000			
SKIP	0.063	0.344	1.000		
GRAFFITI	0.144	0.224	0.515	1.000	
DISRESPE	0.123	0.260	0.521	0.510	1.000

These values represent the standardized variance/covariance matrix at the individual level.

WITHIN LEVEL CORRELATION

	CLOSEKNI	ADULTS	HELP	ALONG_R	SAFE
CLOSEKNI	1.000				
ADULTS	0.439	1.000			
HELP	0.523	0.465	1.000		
ALONG_R	0.202	0.272	0.319	1.000	
SAFE	0.400	0.359	0.476	0.248	1.000
VALUES_R	0.113	0.108	0.181	0.304	0.157
TRUST	0.423	0.463	0.545	0.290	0.542
SKIP	0.298	0.286	0.404	0.192	0.278
GRAFFITI	0.221	0.210	0.270	0.157	0.324
DISRESPE	0.268	0.199	0.287	0.144	0.247

WITHIN LEVEL CORRELATION

	VALUES_R	TRUST	SKIP	GRAFFITI	DISRESPE
VALUES_R	1.000				
TRUST	0.242	1.000			
SKIP	0.063	0.344	1.000		
GRAFFITI	0.144	0.224	0.515	1.000	
DISRESPE	0.123	0.260	0.521	0.510	1.000

These values represent the sample variances and covariances at the neighborhood level. High values indicate greater levels of shared variance among the items. It is important to note that these values differ than those found in the within level variance/covariance matrix.

BETWEEN LEVEL VARIANCE/COVARIANCE

	CLOSEKNI	ADULTS	HELP	ALONG_R	SAFE
CLOSEKNI	0.126				
ADULTS	0.161	0.339			
HELP	0.121	0.203	0.166		
ALONG_R	0.094	0.205	0.145	0.174	
SAFE	0.097	0.173	0.133	0.126	0.126
VALUES_R	0.080	0.142	0.097	0.139	0.105
TRUST	0.126	0.233	0.168	0.183	0.165
SKIP	0.090	0.129	0.123	0.117	0.116
GRAFFITI	0.153	0.297	0.226	0.240	0.209
DISRESPE	0.058	0.036	0.063	0.062	0.039

BETWEEN LEVEL VARIANCE/COVARIANCE

	VALUES_R	TRUST	SKIP	GRAFFITI	DISRESPE
VALUES_R	0.210				
TRUST	0.135	0.247			
SKIP	0.113	0.144	0.151		
GRAFFITI	0.213	0.278	0.177	0.426	
DISRESPE	0.039	0.065	0.077	0.089	0.102

These values represent the standardized variance/covariance matrix at the neighborhood level.

BETWEEN LEVEL CORRELATION

	CLOSEKNI	ADULTS	HELP	ALONG_R	SAFE
CLOSEKNI	1.000				
ADULTS	0.779	1.000			
HELP	0.837	0.858	1.000		
ALONG_R	0.638	0.844	0.858	1.000	
SAFE	0.773	0.837	0.920	0.854	1.000
VALUES_R	0.493	0.533	0.520	0.730	0.644
TRUST	0.716	0.807	0.829	0.884	0.934
SKIP	0.650	0.569	0.775	0.725	0.841
GRAFFITI	0.660	0.781	0.849	0.882	0.903
DISRESPE	0.516	0.196	0.482	0.469	0.341

BETWEEN LEVEL CORRELATION

	VALUES_R	TRUST	SKIP	GRAFFITI	DISRESPE
VALUES_R	1.000				
TRUST	0.593	1.000			
SKIP	0.634	0.745	1.000		
GRAFFITI	0.711	0.857	0.698	1.000	
DISRESPE	0.267	0.408	0.622	0.426	1.000

Given that MPlus calculates all possible factor combinations, error messages commonly appear here. An example of one such error message is shown below. These error messages signal that some of the models (particularly those with 4 or more factors at either level) could not be estimated. This is likely due to insufficient variance in the items to warrant a 4+ factor structure.

STANDARD ERRORS COULD NOT BE COMPUTED.  
PROBLEM OCCURRED IN EXPLORATORY FACTOR ANALYSIS  
WITH 4 WITHIN FACTOR(S) AND 1 BETWEEN FACTOR(S).

THIS PROBLEM IS MOST LIKELY CAUSED BY THE RESIDUAL VARIANCE OF SAFE  
ON THE WITHIN LEVEL CONVERGING TO ZERO.

CHI-SQUARE TEST COULD NOT BE COMPUTED.  
PROBLEM OCCURRED IN EXPLORATORY FACTOR ANALYSIS WITH  
4 WITHIN FACTOR(S) AND 1 BETWEEN FACTOR(S).

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Note: Some of the Mplus output has been eliminated to shorten the document and improve the ease of use.

EXPLORATORY FACTOR ANALYSIS WITH 1 WITHIN FACTOR(S) AND 1 BETWEEN FACTOR(S) :

MODEL FIT INFORMATION

Number of Free Parameters	70
Chi-Square Test of Model Fit	
Value	1388.598*
Degrees of Freedom	70
P-Value	0.0000

These are the results of the EFA with 1 within factor and 1 between factor.

Fit statistics and factor loadings are provided separately for each factor configuration. As shown below, factor loadings are provided at each level.

\* 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	0.121	
90 Percent C.I.	0.115	0.126
Probability RMSEA <= .05	0.000	

RMSEA summarizes the extent to which the model is a good approximation of the observed data. Values below 0.05 indicate close fit. Values above 0.10 indicate poor fit.

CFI/TLI

CFI	0.749
TLI	0.677

Chi-Square Test of Model Fit for the Baseline Model

Value	5338.537
Degrees of Freedom	90
P-Value	0.0000

The CFI and TLI are measures of model fit. They have a range from 0 to 1, with higher values indicating better fit.

SRMR (Standardized Root Mean Square Residual)

Value for Within	0.084
Value for Between	0.068

The SRMR is the only value provided separately at the within- and between-level. The SRMR summarizes the mean absolute value of the correlation residuals for each level. Values below 0.10 are generally acceptable, although values smaller than 0.05 are preferred.

MINIMUM ROTATION FUNCTION VALUE 3.36977

See Kline (2001) for more information on interpretation of fit indices.

WITHIN LEVEL RESULTS

Mplus presents within-level results first.

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

1

CLOSEKNI	0.616*
ADULTS	0.572*
HELP	0.725*
ALONG_R	0.396*
SAFE	0.632*
VALUES_R	0.274*
TRUST	0.699*
SKIP	0.630*
GRAFFITI	0.583*
DISRESPE	0.528*

These loadings represent the linear combination of variables that make-up a factor. Loadings for EFA are in standard deviation units.

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

1

1      1.000

The residual variances are the variances of the items after accounting for all of the variance in the EFA model. Thus, they are the percentage of variance unexplained.

ESTIMATED RESIDUAL VARIANCES

	CLOSEKNI	ADULTS	HELP	ALONG_R	SAFE
1	<u>0.620</u>	<u>0.672</u>	<u>0.474</u>	<u>0.843</u>	<u>0.601</u>

ESTIMATED RESIDUAL VARIANCES

	VALUES_R	TRUST	SKIP	GRAFFITI	DISRESPE
1	<u>0.925</u>	<u>0.512</u>	<u>0.603</u>	<u>0.660</u>	<u>0.721</u>

S.E. GEOMIN ROTATED LOADINGS

1

CLOSEKNI	<u>0.016</u>
ADULTS	0.017
HELP	0.011
ALONG_R	0.021
SAFE	0.016
VALUES_R	0.022
TRUST	0.015
SKIP	0.017
GRAFFITI	0.018
DISRESPE	0.015

S.E. GEOMIN FACTOR CORRELATIONS

1

1      0.000

S.E. ESTIMATED RESIDUAL VARIANCES

	CLOSEKNI	ADULTS	HELP	ALONG_R	SAFE
1	<u>0.020</u>	<u>0.020</u>	<u>0.015</u>	<u>0.017</u>	<u>0.021</u>

S.E. ESTIMATED RESIDUAL VARIANCES

	VALUES_R	TRUST	SKIP	GRAFFITI	DISRESPE
1	<u>0.012</u>	<u>0.020</u>	<u>0.022</u>	<u>0.021</u>	<u>0.016</u>

Est./S.E. GEOMIN ROTATED LOADINGS  
1

CLOSEKNI	38.837
ADULTS	33.555
HELP	68.791
ALONG_R	18.995
SAFE	38.548
VALUES_R	12.591
TRUST	47.865
SKIP	36.681
GRAFFITI	32.806
DISRESPE	35.726

Est./S.E. GEOMIN FACTOR CORRELATIONS  
1

1	0.000
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Est./S.E. ESTIMATED RESIDUAL VARIANCES

	CLOSEKNI	ADULTS	HELP	ALONG_R	SAFE
1	31.699	34.414	30.953	51.059	29.020

Est./S.E. ESTIMATED RESIDUAL VARIANCES

	VALUES_R	TRUST	SKIP	GRAFFITI	DISRESPE
1	77.391	25.091	27.912	31.803	46.241

EXPLORATORY FACTOR ANALYSIS WITH 1 WITHIN FACTOR(S) AND 1 BETWEEN FACTOR(S) :

MINIMUM ROTATION FUNCTION VALUE 7.04738

BETWEEN LEVEL RESULTS

Here is the beginning of the between-level results for the model with 1 factor at each level.

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

	1
CLOSEKNI	0.797*
ADULTS	0.833*
HELP	0.935*
ALONG_R	0.931*
SAFE	0.972*
VALUES_R	0.668*
TRUST	0.924*
SKIP	0.823*
GRAFFITI	0.917*
DISRESPE	0.462*



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

1

1      1.000

ESTIMATED RESIDUAL VARIANCES

	<u>CLOSEKNI</u>	<u>ADULTS</u>	<u>HELP</u>	<u>ALONG_R</u>	<u>SAFE</u>
1	0.365	0.305	0.127	0.133	0.056

ESTIMATED RESIDUAL VARIANCES

	<u>VALUES_R</u>	<u>TRUST</u>	<u>SKIP</u>	<u>GRAFFITI</u>	<u>DISRESPE</u>
1	0.554	0.147	0.322	0.160	0.786

S.E. GEOMIN ROTATED LOADINGS

1

CLOSEKNI	<u>0.072</u>
ADULTS	0.059
HELP	0.043
ALONG_R	0.041
SAFE	0.036
VALUES_R	0.085
TRUST	0.035
SKIP	0.070
GRAFFITI	0.035
DISRESPE	0.125

S.E. GEOMIN FACTOR CORRELATIONS

1

1      0.000

S.E. ESTIMATED RESIDUAL VARIANCES

	<u>CLOSEKNI</u>	<u>ADULTS</u>	<u>HELP</u>	<u>ALONG_R</u>	<u>SAFE</u>
1	0.114	0.098	0.080	0.077	0.070

S.E. ESTIMATED RESIDUAL VARIANCES

	<u>VALUES_R</u>	<u>TRUST</u>	<u>SKIP</u>	<u>GRAFFITI</u>	<u>DISRESPE</u>
1	0.114	0.065	0.115	0.064	0.116

Est./S.E. GEOMIN ROTATED LOADINGS

1

CLOSEKNI	<u>11.119</u>
ADULTS	14.142
HELP	21.892
ALONG_R	22.481
SAFE	26.882
VALUES_R	7.836
TRUST	26.128
SKIP	11.775
GRAFFITI	26.116
DISRESPE	3.695

Est./S.E. GEOMIN FACTOR CORRELATIONS

1  
0.000

Est./S.E. ESTIMATED RESIDUAL VARIANCES

	CLOSEKNI	ADULTS	HELP	ALONG_R	SAFE
1	<u>3.197</u>	<u>3.108</u>	<u>1.586</u>	<u>1.723</u>	<u>0.791</u>

Est./S.E. ESTIMATED RESIDUAL VARIANCES

	VALUES_R	TRUST	SKIP	GRAFFITI	DISRESPE
1	<u>4.860</u>	<u>2.246</u>	<u>2.796</u>	<u>2.480</u>	<u>6.795</u>

EXPLORATORY FACTOR ANALYSIS WITH 2 WITHIN FACTOR(S) AND 1 BETWEEN FACTOR(S) :

MODEL FIT INFORMATION

Number of Free Parameters	79
Chi-Square Test of Model Fit	
Value	337.222*
Degrees of Freedom	61
P-Value	0.0000

This is the beginning of the results for a model with 2 within factors and 1 between factor. This solution is presented as our final EFA model, and these results are presented in the paper in Table 4 of the paper.

\* 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	0.059	
90 Percent C.I.	0.053	0.065
Probability RMSEA <= .05	0.007	

CFI/TLI

CFI	0.947
TLI	0.922

The fit indices show improvement from the initial model (1 within factor 1 between factor).

Chi-Square Test of Model Fit for the Baseline Model

Value	5338.537
Degrees of Freedom	90
P-Value	0.0000

SRMR (Standardized Root Mean Square Residual)

Value for Within	0.039
Value for Between	0.068

MINIMUM ROTATION FUNCTION VALUE 0.23948

WITHIN LEVEL RESULTS

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

	1	2
CLOSEKNI	0.618*	0.030
ADULTS	0.642*	-0.034
HELP	0.735*	0.038
ALONG_R	0.418*	-0.008
SAFE	0.630*	0.035
VALUES_R	0.297*	-0.015
TRUST	0.773*	-0.046
SKIP	0.121*	0.662*
GRAFFITI	0.001	0.711*
DISRESPE	-0.010	0.723*

These factor loadings suggest a configuration where the first 7 items load on Factor 1 and the 3 remaining items load on Factor 2. As described in the paper, this solution is consistent with prior research on collective efficacy.

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

	1	2
1	1.000	
2	0.521*	1.000

The correlation between the two within-level factors is 0.521.

ESTIMATED RESIDUAL VARIANCES

	CLOSEKNI	ADULTS	HELP	ALONG_R	SAFE
1	0.598	0.610	0.429	0.829	0.578

ESTIMATED RESIDUAL VARIANCES

	VALUES_R	TRUST	SKIP	GRAFFITI	DISRESPE
1	0.916	0.438	0.464	0.494	0.485

S.E. GEOMIN ROTATED LOADINGS

	1	2
CLOSEKNI	0.027	0.038
ADULTS	0.027	0.037
HELP	0.028	0.044
ALONG_R	0.024	0.018
SAFE	0.025	0.039
VALUES_R	0.031	0.040
TRUST	0.030	0.044
SKIP	0.032	0.027
GRAFFITI	0.011	0.018
DISRESPE	0.026	0.025

S.E. GEOMIN FACTOR CORRELATIONS

	1	2
1	0.000	
2	0.036	0.000

S.E. ESTIMATED RESIDUAL VARIANCES

	CLOSEKNI	ADULTS	HELP	ALONG_R	SAFE
1	0.021	0.023	0.016	0.018	0.020

S.E. ESTIMATED RESIDUAL VARIANCES

	VALUES_R	TRUST	SKIP	GRAFFITI	DISRESPE
1	0.013	0.024	0.025	0.024	0.023

Est./S.E. GEOMIN ROTATED LOADINGS

	1	2
CLOSEKNI	22.626	0.783
ADULTS	24.106	-0.932
HELP	26.480	0.867
ALONG_R	17.676	-0.463
SAFE	25.602	0.916
VALUES_R	9.492	-0.378
TRUST	25.711	-1.056
SKIP	3.850	24.602
GRAFFITI	0.076	40.248
DISRESPE	-0.364	29.407

Est./S.E. GEOMIN FACTOR CORRELATIONS

	1	2
1	0.000	
2	14.299	0.000

Est./S.E. ESTIMATED RESIDUAL VARIANCES

	CLOSEKNI	ADULTS	HELP	ALONG_R	SAFE
1	28.964	26.679	26.112	47.234	29.108

Est./S.E. ESTIMATED RESIDUAL VARIANCES

	VALUES_R	TRUST	SKIP	GRAFFITI	DISRESPE
1	72.645	18.625	18.433	20.985	21.147

FACTOR STRUCTURE

	1	2
CLOSEKNI	0.634	0.352
ADULTS	0.624	0.300
HELP	0.755	0.421
ALONG_R	0.414	0.209
SAFE	0.649	0.363
VALUES_R	0.290	0.140
TRUST	0.748	0.356
SKIP	0.466	0.725
GRAFFITI	0.371	0.711
DISRESPE	0.367	0.718

EXPLORATORY FACTOR ANALYSIS WITH 2 WITHIN FACTOR(S) AND 1 BETWEEN FACTOR(S) :

MINIMUM ROTATION FUNCTION VALUE 7.04741

BETWEEN LEVEL RESULTS

GEOMIN ROTATED LOADINGS (\* significant at 5% level)  
1

CLOSEKNI	0.797*
ADULTS	0.833*
HELP	0.935*
ALONG_R	0.931*
SAFE	0.972*
VALUES_R	0.668*
TRUST	0.924*
SKIP	0.823*
GRAFFITI	0.917*
DISRESPE	0.462*

The between-level factor loadings remain the same as the previous 1 factor between model (as expected).

GEOMIN FACTOR CORRELATIONS (\* significant at 5% level)  
1

1	1.000
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ESTIMATED RESIDUAL VARIANCES

	CLOSEKNI	ADULTS	HELP	ALONG_R	SAFE
1	0.365	0.305	0.127	0.133	0.056

ESTIMATED RESIDUAL VARIANCES

	VALUES_R	TRUST	SKIP	GRAFFITI	DISRESPE
1	0.554	0.147	0.322	0.160	0.786

S.E. GEOMIN ROTATED LOADINGS

1

CLOSEKNI	0.072
ADULTS	0.059
HELP	0.043
ALONG_R	0.041
SAFE	0.036
VALUES_R	0.085
TRUST	0.035
SKIP	0.070
GRAFFITI	0.035
DISRESPE	0.125

S.E. GEOMIN FACTOR CORRELATIONS

	1
1	<u>0.000</u>

S.E. ESTIMATED RESIDUAL VARIANCES

	CLOSEKNI	ADULTS	HELP	ALONG_R	SAFE
1	<u>0.114</u>	<u>0.098</u>	<u>0.080</u>	<u>0.077</u>	<u>0.070</u>

S.E. ESTIMATED RESIDUAL VARIANCES

	VALUES_R	TRUST	SKIP	GRAFFITI	DISRESPE
1	<u>0.114</u>	<u>0.065</u>	<u>0.115</u>	<u>0.064</u>	<u>0.116</u>

Est./S.E. GEOMIN ROTATED LOADINGS

	1
CLOSEKNI	<u>11.119</u>
ADULTS	14.142
HELP	21.892
ALONG_R	22.481
SAFE	26.882
VALUES_R	7.836
TRUST	26.130
SKIP	11.775
GRAFFITI	26.116
DISRESPE	3.695

Est./S.E. GEOMIN FACTOR CORRELATIONS

	1
1	<u>0.000</u>

Est./S.E. ESTIMATED RESIDUAL VARIANCES

	CLOSEKNI	ADULTS	HELP	ALONG_R	SAFE
1	<u>3.197</u>	<u>3.108</u>	<u>1.586</u>	<u>1.723</u>	<u>0.791</u>

Est./S.E. ESTIMATED RESIDUAL VARIANCES

	VALUES_R	TRUST	SKIP	GRAFFITI	DISRESPE
1	<u>4.860</u>	<u>2.246</u>	<u>2.796</u>	<u>2.480</u>	<u>6.795</u>

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Some of the Mplus output has been eliminated to shorten the document and improve the ease of use.

EXPLORATORY FACTOR ANALYSIS WITH 2 WITHIN FACTOR(S) AND 2 BETWEEN FACTOR(S) :

MODEL FIT INFORMATION

Number of Free Parameters 88

This is the beginning of the results for a model with 2 within factors and 2 between factors.

Chi-Square Test of Model Fit

Value 331.008\*  
 Degrees of Freedom 52  
 P-Value 0.0000

\* 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 0.064  
 90 Percent C.I. 0.058 0.071  
 Probability RMSEA <= .05 0.000

CFI/TLI

CFI 0.947  
 TLI 0.908

Model fit improves from the 2 within and 1 between model to the 2 within and 2 between model, but this is to be expected due to increase in the number of freed parameters.

Chi-Square Test of Model Fit for the Baseline Model

Value 5338.537  
 Degrees of Freedom 90  
 P-Value 0.0000

Thus, it is also important to examine factor loadings for interpretability when comparing models.

SRMR (Standardized Root Mean Square Residual)

Value for Within 0.039  
 Value for Between 0.045

MINIMUM ROTATION FUNCTION VALUE 0.23948

WITHIN LEVEL RESULTS

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

	1	2
CLOSEKNI	0.618*	0.030
ADULTS	0.642*	-0.034
HELP	0.735*	0.038
ALONG_R	0.418*	-0.008
SAFE	0.630*	0.035
VALUES_R	0.297*	-0.015
TRUST	0.773*	-0.046
SKIP	0.121*	0.662*
GRAFFITI	0.001	0.711*
DISRESPE	-0.010	0.723*

The within-level factor loadings are identical to the within-level estimates from other models with 2 within factors, as expected.



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

	1	2
1	1.000	
2	0.521*	1.000

ESTIMATED RESIDUAL VARIANCES

	CLOSEKNI	ADULTS	HELP	ALONG_R	SAFE
1	0.598	0.610	0.429	0.829	0.578

ESTIMATED RESIDUAL VARIANCES

	VALUES_R	TRUST	SKIP	GRAFFITI	DISRESPE
1	0.916	0.438	0.464	0.494	0.485

S.E. GEOMIN ROTATED LOADINGS

	1	2
CLOSEKNI	0.027	0.038
ADULTS	0.027	0.037
HELP	0.028	0.044
ALONG_R	0.024	0.018
SAFE	0.025	0.039
VALUES_R	0.031	0.040
TRUST	0.030	0.044
SKIP	0.032	0.027
GRAFFITI	0.011	0.018
DISRESPE	0.026	0.025

S.E. GEOMIN FACTOR CORRELATIONS

	1	2
1	0.000	
2	0.036	0.000

S.E. ESTIMATED RESIDUAL VARIANCES

	CLOSEKNI	ADULTS	HELP	ALONG_R	SAFE
1	0.021	0.023	0.016	0.018	0.020

S.E. ESTIMATED RESIDUAL VARIANCES

	VALUES_R	TRUST	SKIP	GRAFFITI	DISRESPE
1	0.013	0.024	0.025	0.024	0.023

Est./S.E. GEOMIN ROTATED LOADINGS

	1	2
CLOSEKNI	22.626	0.783
ADULTS	24.106	-0.932
HELP	26.480	0.867
ALONG_R	17.676	-0.463
SAFE	25.602	0.916
VALUES_R	9.492	-0.378
TRUST	25.711	-1.056
SKIP	3.850	24.602
GRAFFITI	0.076	40.248
DISRESPE	-0.364	29.407

Est./S.E. GEOMIN FACTOR CORRELATIONS

	1	2
1	0.000	
2	14.299	0.000

Est./S.E. ESTIMATED RESIDUAL VARIANCES

	CLOSEKNI	ADULTS	HELP	ALONG_R	SAFE
1	28.964	26.679	26.112	47.234	29.108

Est./S.E. ESTIMATED RESIDUAL VARIANCES

	VALUES_R	TRUST	SKIP	GRAFFITI	DISRESPE
1	72.645	18.625	18.433	20.984	21.147

FACTOR STRUCTURE

	1	2
CLOSEKNI	0.634	0.352
ADULTS	0.624	0.300
HELP	0.755	0.421
ALONG_R	0.414	0.209
SAFE	0.649	0.363
VALUES_R	0.290	0.140
TRUST	0.748	0.356
SKIP	0.466	0.725
GRAFFITI	0.371	0.711
DISRESPE	0.367	0.718

EXPLORATORY FACTOR ANALYSIS WITH 2 WITHIN FACTOR(S) AND 2 BETWEEN FACTOR(S) :

MINIMUM ROTATION FUNCTION VALUE 0.44136

BETWEEN LEVEL RESULTS

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

	1	2
CLOSEKNI	0.762*	0.085
ADULTS	0.889*	-0.110
HELP	0.920*	0.033
ALONG_R	0.921*	0.022
SAFE	0.998*	-0.058
VALUES_R	0.676*	-0.019
TRUST	0.928*	-0.009
SKIP	0.771*	0.142
GRAFFITI	0.916*	0.001
DISRESPE	0.000	1.926

The between-level factor loadings show that the first nine items load on the first factor, while only one item loads on the second factor (though this loading is not significant).

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

	1	2
1	1.000	
2	0.238*	1.000

ESTIMATED RESIDUAL VARIANCES

	CLOSEKNI	ADULTS	HELP	ALONG_R	SAFE
1	0.381	0.245	0.138	0.141	0.028

ESTIMATED RESIDUAL VARIANCES

	VALUES_R	TRUST	SKIP	GRAFFITI	DISRESPE
1	0.549	0.143	0.334	0.160	-2.709

S.E. GEOMIN ROTATED LOADINGS

	1	2
CLOSEKNI	0.104	0.184
ADULTS	0.090	0.186
HELP	0.051	0.105
ALONG_R	0.047	0.080
SAFE	0.061	0.116
VALUES_R	0.086	0.086
TRUST	0.032	0.052
SKIP	0.147	0.267
GRAFFITI	0.038	0.026
DISRESPE	0.001	2.860

S.E. GEOMIN FACTOR CORRELATIONS

	1	2
1	<u>0.000</u>	<u>          </u>
2	0.356	0.000

S.E. ESTIMATED RESIDUAL VARIANCES

	CLOSEKNI	ADULTS	HELP	ALONG_R	SAFE
1	<u>0.118</u>	<u>0.085</u>	<u>0.074</u>	<u>0.072</u>	<u>0.074</u>

S.E. ESTIMATED RESIDUAL VARIANCES

	VALUES_R	TRUST	SKIP	GRAFFITI	DISRESPE
1	<u>0.113</u>	<u>0.059</u>	<u>0.116</u>	<u>0.065</u>	<u>11.013</u>

Est./S.E. GEOMIN ROTATED LOADINGS

	1	2
CLOSEKNI	<u>7.313</u>	<u>0.461</u>
ADULTS	9.823	-0.593
HELP	17.996	0.314
ALONG_R	19.786	0.271
SAFE	16.365	-0.497
VALUES_R	7.853	-0.218
TRUST	28.857	-0.181
SKIP	5.233	0.531
GRAFFITI	24.340	0.051
DISRESPE	0.168	0.673

Est./S.E. GEOMIN FACTOR CORRELATIONS

	1	2
1	<u>0.000</u>	<u>          </u>
2	0.668	0.000

Est./S.E. ESTIMATED RESIDUAL VARIANCES

	CLOSEKNI	ADULTS	HELP	ALONG_R	SAFE
1	<u>3.227</u>	<u>2.879</u>	<u>1.876</u>	<u>1.947</u>	<u>0.375</u>

Est./S.E. ESTIMATED RESIDUAL VARIANCES

	VALUES_R	TRUST	SKIP	GRAFFITI	DISRESPE
1	<u>4.840</u>	<u>2.432</u>	<u>2.881</u>	<u>2.445</u>	<u>-0.246</u>

FACTOR STRUCTURE

	1	2
CLOSEKNI	0.783	0.266
ADULTS	0.863	0.101
HELP	0.928	0.252
ALONG_R	0.927	0.241
SAFE	0.984	0.179
VALUES_R	0.671	0.142
TRUST	0.926	0.211
SKIP	0.804	0.325
GRAFFITI	0.917	0.219
DISRESPE	0.458	1.926

## Multilevel Confirmatory Factor Analysis (ML-CFA) Syntax

Mplus VERSION 7  
MUTHEN & MUTHEN

### INPUT INSTRUCTIONS

Title:

CFA SPECIFYING 2 FACTORS WITHIN AND 1 BETWEEN

Data:

File is ML\_EFA\_CFA\_06\_27.dat ;

Variable:

Names are	caseid	SAMPID_N	hhid	pid	RSA_TYPE	wgtrs
wgtadlt	wgtpcg	closekni	adults	help	along	
safe	values	trust	AB6_8	AB6_9	CLOSEKNI0	
skip	graffiti	disrespe	AB8_1	AB8_2	AB9	
AB11_1	AB11_2	AB11_3	AB12	AB13	AB14	
tractx	sample1	ALONG_r	VALUES_r	AGE_YR	sex	
RB1	RB2_1	RB2_2	RB2_3	RB2_4	RB2_5	
RB2_6	AJ5	movsince	HA18_1			

Missing are . ;

USEOBSERVATIONS = sample1 == 0;

USEVARIABLES = closekni adults help along\_r  
safe values\_r trust skip graffiti disrespe;

CATEGORICAL = closekni adults help along\_r  
safe values\_r trust skip graffiti disrespe;

CLUSTER = tractx;  
WEIGHT = WGTADLT;

Analysis:

Type = twolevel;  
ESTIMATOR=WLSMV;

Model:

%within%

```
cohesion by closekni;  
cohesion by adults;  
cohesion by help;  
cohesion by along_r;  
cohesion by safe;  
cohesion by values_r;  
cohesion by trust;
```

```
control by skip;
```

Here we are using the other half of the split sample for the CFA.

CLUSTER refers to the cluster variable (tractx = Census tract ID).

Type = twolevel specifies a multilevel model where the within-level and between-level variance/covariance matrices are separately analyzed.

As noted in the EFA, we are using the WLSMV estimator because we are analyzing data from categorical indicators.

Based on the results of the EFA, we estimate a 2-factor structure at the within level, corresponding to "social cohesion" and "informal social control."

Although not shown here, start values may be needed if the model does not run in a reasonable amount of time. Within level starting values can come from a single-level CFA, where the factor analysis is conducted at only one level and the clustering of observations is accounted for through the TYPE=complex command.

For each factor, one loading must be fixed at 1 to allow for model identification. Here, the first factor loading is fixed to 1 as the default in Mplus.

```
control by graffiti;  
control by disrespe;  
  
cohesion WITH control;  
  
cohesion;  
control;
```

Factor variances and covariances are freely estimated at the within level. This is apparent by the lack of constraints imposed on these models.

```
%between%
```

```
col_eff by closekni adults help along_r  
safe values_r trust skip graffiti disrespe;
```

Based on the results of the EFA, we are estimating a 1-factor structure at the between level.

```
OUTPUT:
```

```
sampstat STDYX Residual;
```

```
SAVEDATA:
```

```
swmatrix is cfa_swmatrix.dat;
```

Although not shown, starting values can be provided to expedite processing. Start values can be obtained by including SVALUES in the output statement. Between level start values can come from the factor loadings obtained from a multi-level EFA with 1 factor loading on the between-level.

The savedata command asks Mplus to create swmatrix file containing the sample statistics at the within and between levels for the CFA sample. This is useful in reducing computing time in subsequent models using the same sample.

## Multilevel Confirmatory Factor Analysis (ML-CFA) Results

This is the beginning of the output for our CFA model that is presented in Table 5.

### SUMMARY OF ANALYSIS

Number of groups	1
Number of observations	1303
Number of dependent variables	10
Number of independent variables	0
Number of continuous latent variables	3
Observed dependent variables	
Binary and ordered categorical (ordinal)	
CLOSEKNI	ADULTS
TRUST	SKIP
HELP	GRAFFITI
ALONG_R	DISRESPE
SAFE	VALUES_R
Continuous latent variables	
COHESION	CONTROL
COL_EFF	
Variables with special functions	
Cluster variable	TRACTX
Weight variable (cluster-size scaling)	
WGTADLT	
Estimator	WLSMV
Optimization Specifications for the Quasi-Newton Algorithm for Continuous Outcomes	
Maximum number of iterations	1000
Convergence criterion	0.100D-05
Optimization Specifications for the EM Algorithm	
Maximum number of iterations	500
Convergence criteria	
Loglikelihood change	0.100D-02
Relative loglikelihood change	0.100D-05
Derivative	0.100D-02
Optimization Specifications for the M step of the EM Algorithm for Categorical Latent variables	
Number of M step iterations	1
M step convergence criterion	0.100D-02
Basis for M step termination	ITERATION
Optimization Specifications for the M step of the EM Algorithm for Censored, Binary or Ordered Categorical (Ordinal), Unordered Categorical (Nominal) and Count Outcomes	
Number of M step iterations	1
M step convergence criterion	0.100D-02
Basis for M step termination	ITERATION
Maximum value for logit thresholds	10
Minimum value for logit thresholds	-10
Minimum expected cell size for chi-square	0.100D-01
Maximum number of iterations for H1	2000
Convergence criterion for H1	0.100D-03
Optimization algorithm	FS
Integration Specifications	
Type	STANDARD
Number of integration points	7
Dimensions of numerical integration	2
Adaptive quadrature	ON
Link	PROBIT
Cholesky	ON



Input data file(s)  
 ML\_EFA\_CFA\_06\_27.dat  
 Input data format FREE

SUMMARY OF DATA

Number of clusters 65  
 Average cluster size 20.046  
 Estimated Intraclass Correlations for the Y Variables

Variable	Intraclass Correlation	Variable	Intraclass Correlation	Variable	Intraclass Correlation
CLOSEKNI	0.121	ADULTS	0.216	HELP	0.174
ALONG_R	0.178	SAFE	0.089	VALUES_R	0.114
TRUST	0.254	SKIP	0.125	GRAFFITI	0.273
DISRESPE	0.090				

These ICCs represent the between-level variance divided by the total variance for each item. Near-zero ICCs suggest minimal neighborhood-based associations.

COVARIANCE COVERAGE OF DATA

Minimum covariance coverage value 0.100

UNIVARIATE PROPORTIONS AND COUNTS FOR CATEGORICAL VARIABLES

CLOSEKNI		
Category 1	0.063	82.257
Category 2	0.456	594.495
Category 3	0.059	76.525
Category 4	0.378	492.565
Category 5	0.044	57.158
ADULTS		
Category 1	0.065	84.773
Category 2	0.542	706.162
Category 3	0.128	167.001
Category 4	0.241	314.254
Category 5	0.024	30.810
HELP		
Category 1	0.104	135.301
Category 2	0.660	859.470
Category 3	0.063	82.294
Category 4	0.149	194.529
Category 5	0.024	31.405
ALONG_R		
Category 1	0.085	110.708
Category 2	0.596	776.644
Category 3	0.096	124.768
Category 4	0.198	258.423
Category 5	0.025	32.457
SAFE		
Category 1	0.085	111.263
Category 2	0.623	812.207
Category 3	0.106	137.679
Category 4	0.152	198.629
Category 5	0.033	43.222
VALUES_R		
Category 1	0.036	46.529

It is useful to compare this output to frequency counts from the data file used for initial data management in Stata, SAS or SPSS.  
  
 This ensures that the variables were correctly pulled in to Mplus.

Category 2	0.455	593.188
Category 3	0.122	159.053
Category 4	0.347	451.771
Category 5	0.040	52.458
TRUST		
Category 1	0.043	56.042
Category 2	0.607	791.541
Category 3	0.118	153.238
Category 4	0.203	265.062
Category 5	0.028	37.118
SKIP		
Category 1	0.217	282.169
Category 2	0.390	508.143
Category 3	0.063	81.787
Category 4	0.236	307.307
Category 5	0.095	123.595
GRAFFITI		
Category 1	0.388	505.255
Category 2	0.345	449.308
Category 3	0.046	59.931
Category 4	0.160	208.419
Category 5	0.061	80.087
DISRESPE		
Category 1	0.168	218.540
Category 2	0.393	512.093
Category 3	0.103	134.355
Category 4	0.247	321.480
Category 5	0.089	116.531

SAMPLE STATISTICS

ESTIMATED SAMPLE STATISTICS

Note: Thresholds are a component of the estimation of models with categorical indicators. Thresholds refer to the amount of the distribution of a latent, underlying continuous version of each ordered categorical item must respond in a certain category of the observed ordinal item.

	MEANS/INTERCEPTS/THRESHOLDS				
	CLOSEKNI	CLOSEKNI	CLOSEKNI	CLOSEKNI	ADULTS\$1
1	-1.631	0.056	0.215	1.820	-1.707
	MEANS/INTERCEPTS/THRESHOLDS				
	ADULTS\$2	ADULTS\$3	ADULTS\$4	HELP\$1	HELP\$2
1	0.311	0.719	2.214	-1.389	0.789
	MEANS/INTERCEPTS/THRESHOLDS				
	HELP\$3	HELP\$4	ALONG_R\$	ALONG_R\$	ALONG_R\$
1	1.032	2.161	-1.514	0.539	0.857
	MEANS/INTERCEPTS/THRESHOLDS				
	ALONG_R\$	SAFE\$1	SAFE\$2	SAFE\$3	SAFE\$4
1	2.132	-1.429	0.585	0.944	1.929
	MEANS/INTERCEPTS/THRESHOLDS				
	VALUES_R	VALUES_R	VALUES_R	VALUES_R	TRUST\$1
1	-1.909	-0.013	0.317	1.859	-1.981

MEANS/INTERCEPTS/THRESHOLDS					
	TRUST\$2	TRUST\$3	TRUST\$4	SKIP\$1	SKIP\$2
1	0.462	0.864	2.172	-0.831	0.299

MEANS/INTERCEPTS/THRESHOLDS					
	SKIP\$3	SKIP\$4	GRAFFITI	GRAFFITI	GRAFFITI
1	0.480	1.413	-0.302	0.753	0.919

MEANS/INTERCEPTS/THRESHOLDS					
	GRAFFITI	DISRESPE	DISRESPE	DISRESPE	DISRESPE
1	1.783	-1.003	0.162	0.445	1.415

These values represent the sample variances and covariances across individuals, within neighborhoods. High values indicate greater levels of shared variance among the items.

WITHIN LEVEL VARIANCE/COVARIANCE

	CLOSEKNI	ADULTS	HELP	ALONG_R	SAFE
CLOSEKNI	1.000				
ADULTS	0.455	1.000			
HELP	0.453	0.475	1.000		
ALONG_R	0.201	0.314	0.391	1.000	
SAFE	0.407	0.412	0.444	0.243	1.000
VALUES_R	0.194	0.058	0.137	0.335	0.125
TRUST	0.389	0.397	0.516	0.329	0.414
SKIP	0.252	0.157	0.235	0.169	0.401
GRAFFITI	0.202	0.273	0.289	0.246	0.377
DISRESPE	0.290	0.188	0.273	0.224	0.276

WITHIN LEVEL VARIANCE/COVARIANCE

	VALUES_R	TRUST	SKIP	GRAFFITI	DISRESPE
VALUES_R	1.000				
TRUST	0.207	1.000			
SKIP	0.166	0.373	1.000		
GRAFFITI	0.152	0.348	0.581	1.000	
DISRESPE	0.113	0.296	0.420	0.459	1.000

These values represent the standardized variance/covariance matrix at the individual level.

WITHIN LEVEL CORRELATION

	CLOSEKNI	ADULTS	HELP	ALONG_R	SAFE
CLOSEKNI	1.000				
ADULTS	0.455	1.000			
HELP	0.453	0.475	1.000		
ALONG_R	0.201	0.314	0.391	1.000	
SAFE	0.407	0.412	0.444	0.243	1.000
VALUES_R	0.194	0.058	0.137	0.335	0.125
TRUST	0.389	0.397	0.516	0.329	0.414
SKIP	0.252	0.157	0.235	0.169	0.401
GRAFFITI	0.202	0.273	0.289	0.246	0.377
DISRESPE	0.290	0.188	0.273	0.224	0.276

WITHIN LEVEL CORRELATION					
	VALUES_R	TRUST	SKIP	GRAFFITI	DISRESPE
VALUES_R	1.000				
TRUST	0.207	1.000			
SKIP	0.166	0.373	1.000		
GRAFFITI	0.152	0.348	0.581	1.000	
DISRESPE	0.113	0.296	0.420	0.459	1.000

These values represent the sample variances and covariances across neighborhoods. High values indicate greater levels of shared variance among the items.

BETWEEN LEVEL VARIANCE/COVARIANCE					
	CLOSEKNI	ADULTS	HELP	ALONG_R	SAFE
CLOSEKNI	0.137				
ADULTS	0.134	0.275			
HELP	0.109	0.183	0.211		
ALONG_R	0.093	0.160	0.168	0.216	
SAFE	0.068	0.102	0.110	0.097	0.097
VALUES_R	0.071	0.115	0.121	0.132	0.074
TRUST	0.151	0.224	0.220	0.209	0.153
SKIP	0.094	0.100	0.068	0.089	0.072
GRAFFITI	0.166	0.264	0.206	0.231	0.142
DISRESPE	0.058	0.055	0.055	0.035	0.018

BETWEEN LEVEL VARIANCE/COVARIANCE					
	VALUES_R	TRUST	SKIP	GRAFFITI	DISRESPE
VALUES_R	0.128				
TRUST	0.150	0.341			
SKIP	0.079	0.125	0.143		
GRAFFITI	0.149	0.292	0.176	0.376	
DISRESPE	0.042	0.032	0.035	0.046	0.099

These values represent the standardized variance/covariance matrix at the neighborhood level.

BETWEEN LEVEL CORRELATION					
	CLOSEKNI	ADULTS	HELP	ALONG_R	SAFE
CLOSEKNI	1.000				
ADULTS	0.691	1.000			
HELP	0.642	0.760	1.000		
ALONG_R	0.540	0.657	0.789	1.000	
SAFE	0.592	0.625	0.767	0.667	1.000
VALUES_R	0.537	0.616	0.738	0.796	0.662
TRUST	0.698	0.732	0.820	0.769	0.842
SKIP	0.670	0.504	0.392	0.507	0.611
GRAFFITI	0.731	0.820	0.733	0.809	0.741
DISRESPE	0.498	0.332	0.384	0.241	0.182

	BETWEEN LEVEL CORRELATION				
	VALUES_R	TRUST	SKIP	GRAFFITI	DISRESPE
VALUES_R	1.000				
TRUST	0.716	1.000			
SKIP	0.587	0.565	1.000		
GRAFFITI	0.678	0.814	0.759	1.000	
DISRESPE	0.374	0.175	0.292	0.239	1.000

THE MODEL ESTIMATION TERMINATED NORMALLY

MODEL FIT INFORMATION

Number of Free Parameters 71

Chi-Square Test of Model Fit

Value	629.816*
Degrees of Freedom	69
P-Value	0.0000

\* 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	0.079
----------	-------

CFI/TLI

CFI	0.903
TLI	0.874

RMSEA summarizes the extent to which the model is a good approximation of the observed data. Values below 0.05 indicate close fit. Values above 0.10 indicate poor fit.

Chi-Square Test of Model Fit for the Baseline Model

Value	5899.990
Degrees of Freedom	90
P-Value	0.0000

The CFI and TLI are measures of model fit. They have a range from 0 to 1, with higher values indicating better fit.

SRMR (Standardized Root Mean Square Residual)

Value for Within	0.054
Value for Between	0.073

The SRMR is the only value provided separately at the within- and between-level. The SRMR summarizes the mean absolute value of the correlation residuals for each level. Values below 0.10 are generally acceptable, although values smaller than 0.05 are preferred.

WRMR (Weighted Root Mean Square Residual)

Value	1.694
-------	-------

See Kline (2001) for more information on interpretation of fit indices.

MODEL RESULTS

	Estimate	S.E.	Est./S.E.	Two-Tailed P-Value
Within Level				
COHESION BY				
CLOSEKNI	1.000	0.000	999.000	999.000
ADULTS	1.023	0.081	12.692	0.000
HELP	1.236	0.065	19.098	0.000
ALONG_R	0.677	0.043	15.724	0.000
SAFE	1.074	0.054	19.834	0.000
VALUES_R	0.348	0.030	11.413	0.000
TRUST	1.169	0.069	16.889	0.000
CONTROL BY				
SKIP	1.000	0.000	999.000	999.000
GRAFFITI	1.146	0.082	13.908	0.000
DISRESPE	0.738	0.055	13.434	0.000
COHESION WITH CONTROL				
	0.524	0.037	14.194	0.000
Variances				
COHESION	0.633	0.055	11.558	0.000
CONTROL	1.104	0.096	11.450	0.000
Between Level				
COL_EFF BY				
CLOSEKNI	1.000	0.000	999.000	999.000
ADULTS	1.520	0.399	3.810	0.000
HELP	1.505	0.392	3.837	0.000
ALONG_R	1.193	0.387	3.081	0.002
SAFE	0.916	0.235	3.905	0.000
VALUES_R	0.817	0.248	3.291	0.001
TRUST	1.951	0.517	3.777	0.000
SKIP	0.999	0.249	4.012	0.000
GRAFFITI	2.433	0.566	4.302	0.000
DISRESPE	0.384	0.155	2.469	0.014
Thresholds				
CLOSEKNI\$1	-2.084	0.089	-23.394	0.000
CLOSEKNI\$2	0.071	0.072	0.983	0.325
CLOSEKNI\$3	0.274	0.076	3.624	0.000
CLOSEKNI\$4	2.326	0.096	24.351	0.000
ADULTS\$1	-2.202	0.127	-17.316	0.000
ADULTS\$2	0.401	0.103	3.905	0.000
ADULTS\$3	0.928	0.098	9.505	0.000
ADULTS\$4	2.855	0.147	19.453	0.000
HELP\$1	-1.948	0.114	-17.152	0.000
HELP\$2	1.106	0.099	11.202	0.000
HELP\$3	1.447	0.099	14.648	0.000
HELP\$4	3.030	0.106	28.615	0.000
ALONG_R\$1	-1.719	0.094	-18.200	0.000
ALONG_R\$2	0.612	0.084	7.317	0.000
ALONG_R\$3	0.973	0.088	11.082	0.000
ALONG_R\$4	2.421	0.111	21.729	0.000
SAFE\$1	-1.880	0.079	-23.660	0.000
SAFE\$2	0.769	0.074	10.457	0.000
SAFE\$3	1.242	0.077	16.102	0.000
SAFE\$4	2.537	0.089	28.489	0.000

These are the unstandardized model results. Each estimate represents a factor loading or "lambda" coefficient. Each loading can be interpreted similarly to a beta coefficient from a regression analysis.

By default, Mplus constrains the first factor loading for each factor to 1.

VALUES_R\$1	-1.981	0.073	-26.998	0.000
VALUES_R\$2	-0.013	0.058	-0.226	0.821
VALUES_R\$3	0.329	0.059	5.624	0.000
VALUES_R\$4	1.929	0.074	26.111	0.000
TRUST\$1	-2.706	0.158	-17.082	0.000
TRUST\$2	0.631	0.119	5.321	0.000
TRUST\$3	1.180	0.122	9.708	0.000
TRUST\$4	2.967	0.137	21.616	0.000
SKIP\$1	-1.205	0.090	-13.379	0.000
SKIP\$2	0.434	0.091	4.785	0.000
SKIP\$3	0.696	0.089	7.835	0.000
SKIP\$4	2.049	0.110	18.580	0.000
GRAFFITI\$1	-0.473	0.147	-3.223	0.001
GRAFFITI\$2	1.180	0.154	7.658	0.000
GRAFFITI\$3	1.439	0.152	9.473	0.000
GRAFFITI\$4	2.791	0.160	17.463	0.000
DISRESPE\$1	-1.270	0.073	-17.353	0.000
DISRESPE\$2	0.205	0.066	3.129	0.002
DISRESPE\$3	0.563	0.066	8.552	0.000
DISRESPE\$4	1.791	0.073	24.481	0.000
Variances				
COL_EFF	0.134	0.064	2.104	0.035
Residual Variances				
CLOSEKNI	0.090	0.030	3.044	0.002
ADULTS	0.146	0.041	3.607	0.000
HELP	0.110	0.037	2.952	0.003
ALONG_R	0.088	0.027	3.195	0.001
SAFE	0.055	0.022	2.489	0.013
VALUES_R	0.048	0.019	2.538	0.011
TRUST	0.125	0.045	2.751	0.006
SKIP	0.167	0.046	3.669	0.000
GRAFFITI	0.127	0.069	1.849	0.064
DISRESPE	0.139	0.042	3.329	0.001

STANDARDIZED MODEL RESULTS

STDYX Standardization

These are the standardized model results, which are presented in Table 5. Each loading can be interpreted similarly to a regression coefficient in standard deviation units.

	Estimate	S.E.	Est./S.E.	Two-Tailed P-Value
Within Level				
COHESION BY				
CLOSEKNI	0.622	0.016	37.736	0.000
ADULTS	0.631	0.019	32.775	0.000
HELP	0.701	0.014	49.943	0.000
ALONG_R	0.474	0.017	28.612	0.000
SAFE	0.649	0.015	42.788	0.000
VALUES_R	0.266	0.018	14.625	0.000
TRUST	0.681	0.015	46.453	0.000
CONTROL BY				
SKIP	0.724	0.015	48.186	0.000
GRAFFITI	0.769	0.017	45.883	0.000
DISRESPE	0.613	0.020	31.102	0.000

COHESION WITH CONTROL	0.627	0.020	32.147	0.000
Variances				
COHESION	1.000	0.000	999.000	999.000
CONTROL	1.000	0.000	999.000	999.000
Between Level				
COL_EFF BY				
CLOSEKNI	0.774	0.073	10.632	0.000
ADULTS	0.824	0.053	15.645	0.000
HELP	0.857	0.054	15.775	0.000
ALONG_R	0.828	0.066	12.585	0.000
SAFE	0.819	0.063	12.946	0.000
VALUES_R	0.807	0.070	11.501	0.000
TRUST	0.897	0.053	17.049	0.000
SKIP	0.667	0.082	8.152	0.000
GRAFFITI	0.928	0.038	24.268	0.000
DISRESPE	0.353	0.127	2.782	0.005
Thresholds				
CLOSEKNI\$1	-1.631	0.069	-23.640	0.000
CLOSEKNI\$2	0.056	0.057	0.985	0.325
CLOSEKNI\$3	0.215	0.059	3.645	0.000
CLOSEKNI\$4	1.820	0.072	25.303	0.000
ADULTS\$1	-1.707	0.093	-18.413	0.000
ADULTS\$2	0.311	0.081	3.847	0.000
ADULTS\$3	0.719	0.078	9.239	0.000
ADULTS\$4	2.214	0.119	18.559	0.000
HELP\$1	-1.389	0.079	-17.681	0.000
HELP\$2	0.789	0.071	11.060	0.000
HELP\$3	1.032	0.071	14.481	0.000
HELP\$4	2.161	0.077	27.891	0.000
ALONG_R\$1	-1.514	0.083	-18.300	0.000
ALONG_R\$2	0.539	0.074	7.296	0.000
ALONG_R\$3	0.857	0.077	11.056	0.000
ALONG_R\$4	2.132	0.100	21.254	0.000
SAFE\$1	-1.429	0.062	-23.224	0.000
SAFE\$2	0.585	0.055	10.708	0.000
SAFE\$3	0.944	0.057	16.599	0.000
SAFE\$4	1.929	0.062	30.871	0.000
VALUES_R\$1	-1.909	0.071	-26.889	0.000
VALUES_R\$2	-0.013	0.056	-0.226	0.821
VALUES_R\$3	0.317	0.056	5.640	0.000
VALUES_R\$4	1.859	0.070	26.486	0.000
TRUST\$1	-1.981	0.114	-17.372	0.000
TRUST\$2	0.462	0.087	5.335	0.000
TRUST\$3	0.864	0.088	9.808	0.000
TRUST\$4	2.172	0.104	20.796	0.000
SKIP\$1	-0.831	0.065	-12.846	0.000
SKIP\$2	0.299	0.061	4.908	0.000
SKIP\$3	0.480	0.059	8.196	0.000
SKIP\$4	1.413	0.066	21.467	0.000
GRAFFITI\$1	-0.302	0.092	-3.285	0.001
GRAFFITI\$2	0.753	0.101	7.466	0.000
GRAFFITI\$3	0.919	0.100	9.224	0.000
GRAFFITI\$4	1.783	0.108	16.470	0.000
DISRESPE\$1	-1.003	0.055	-18.204	0.000
DISRESPE\$2	0.162	0.052	3.128	0.002
DISRESPE\$3	0.445	0.052	8.593	0.000
DISRESPE\$4	1.415	0.054	26.211	0.000



Variances					
COL_EFF	1.000	0.000	999.000	999.000	

Residual Variances

CLOSEKNI	0.401	0.113	3.555	0.000
ADULTS	0.320	0.087	3.689	0.000
HELP	0.265	0.093	2.850	0.004
ALONG_R	0.314	0.109	2.882	0.004
SAFE	0.329	0.104	3.173	0.002
VALUES_R	0.349	0.113	3.088	0.002
TRUST	0.196	0.094	2.080	0.038
SKIP	0.555	0.109	5.082	0.000
GRAFFITI	0.138	0.071	1.943	0.052
DISRESPE	0.875	0.090	9.781	0.000

R-SQUARE

Within Level

Observed Variable	Estimate	S.E.	Est./S.E.	Two-Tailed P-Value	Scale Factors
CLOSEKNI	0.387	0.021	18.868	0.000	0.783
ADULTS	0.398	0.024	16.388	0.000	0.776
HELP	0.491	0.020	24.971	0.000	0.713
ALONG_R	0.225	0.016	14.306	0.000	0.880
SAFE	0.422	0.020	21.394	0.000	0.760
VALUES_R	0.071	0.010	7.313	0.000	0.964
TRUST	0.464	0.020	23.227	0.000	0.732
SKIP	0.525	0.022	24.093	0.000	0.689
GRAFFITI	0.592	0.026	22.941	0.000	0.639
DISRESPE	0.376	0.024	15.551	0.000	0.790

Between Level

Observed Variable	Estimate	S.E.	Est./S.E.	Two-Tailed P-Value
CLOSEKNI	0.599	0.113	5.316	0.000
ADULTS	0.680	0.087	7.822	0.000
HELP	0.735	0.093	7.887	0.000
ALONG_R	0.686	0.109	6.292	0.000
SAFE	0.671	0.104	6.473	0.000
VALUES_R	0.651	0.113	5.750	0.000
TRUST	0.804	0.094	8.525	0.000
SKIP	0.445	0.109	4.076	0.000
GRAFFITI	0.862	0.071	12.134	0.000
DISRESPE	0.125	0.090	1.391	0.164

QUALITY OF NUMERICAL RESULTS

Condition Number for the Information Matrix (ratio of smallest to largest eigenvalue) 0.130E-03

RESIDUAL OUTPUT

ESTIMATED MODEL AND RESIDUALS (OBSERVED - ESTIMATED)

	Model Estimated	Means/Intercepts/Thresholds			
	CLOSEKNI	CLOSEKNI	CLOSEKNI	CLOSEKNI	ADULTS\$1
1	<u>-1.631</u>	<u>0.056</u>	<u>0.215</u>	<u>1.820</u>	<u>-1.707</u>
	Model Estimated	Means/Intercepts/Thresholds			
	ADULTS\$2	ADULTS\$3	ADULTS\$4	HELP\$1	HELP\$2
1	<u>0.311</u>	<u>0.719</u>	<u>2.214</u>	<u>-1.389</u>	<u>0.789</u>
	Model Estimated	Means/Intercepts/Thresholds			
	HELP\$3	HELP\$4	ALONG_R\$	ALONG_R\$	ALONG_R\$
1	<u>1.032</u>	<u>2.161</u>	<u>-1.514</u>	<u>0.539</u>	<u>0.857</u>
	Model Estimated	Means/Intercepts/Thresholds			
	ALONG_R\$	SAFE\$1	SAFE\$2	SAFE\$3	SAFE\$4
1	<u>2.132</u>	<u>-1.429</u>	<u>0.585</u>	<u>0.944</u>	<u>1.929</u>
	Model Estimated	Means/Intercepts/Thresholds			
	VALUES_R	VALUES_R	VALUES_R	VALUES_R	TRUST\$1
1	<u>-1.909</u>	<u>-0.013</u>	<u>0.317</u>	<u>1.859</u>	<u>-1.981</u>
	Model Estimated	Means/Intercepts/Thresholds			
	TRUST\$2	TRUST\$3	TRUST\$4	SKIP\$1	SKIP\$2
1	<u>0.462</u>	<u>0.864</u>	<u>2.172</u>	<u>-0.831</u>	<u>0.299</u>
	Model Estimated	Means/Intercepts/Thresholds			
	SKIP\$3	SKIP\$4	GRAFFITI	GRAFFITI	GRAFFITI
1	<u>0.480</u>	<u>1.413</u>	<u>-0.302</u>	<u>0.753</u>	<u>0.919</u>
	Model Estimated	Means/Intercepts/Thresholds			
	GRAFFITI	DISRESPE	DISRESPE	DISRESPE	DISRESPE
1	<u>1.783</u>	<u>-1.003</u>	<u>0.162</u>	<u>0.445</u>	<u>1.415</u>
	Residuals for	Means/Intercepts/Thresholds			
	CLOSEKNI	CLOSEKNI	CLOSEKNI	CLOSEKNI	ADULTS\$1
1	<u>0.000</u>	<u>0.000</u>	<u>0.000</u>	<u>0.000</u>	<u>0.000</u>
	Residuals for	Means/Intercepts/Thresholds			
	ADULTS\$2	ADULTS\$3	ADULTS\$4	HELP\$1	HELP\$2
1	<u>0.000</u>	<u>0.000</u>	<u>0.000</u>	<u>0.000</u>	<u>0.000</u>

	Residuals for Means/Intercepts/Thresholds				
	HELP\$3	HELP\$4	ALONG_R\$	ALONG_R\$	ALONG_R\$
1	<u>0.000</u>	<u>0.000</u>	<u>0.000</u>	<u>0.000</u>	<u>0.000</u>

	Residuals for Means/Intercepts/Thresholds				
	ALONG_R\$	SAFE\$1	SAFE\$2	SAFE\$3	SAFE\$4
1	<u>0.000</u>	<u>0.000</u>	<u>0.000</u>	<u>0.000</u>	<u>0.000</u>

	Residuals for Means/Intercepts/Thresholds				
	VALUES_R	VALUES_R	VALUES_R	VALUES_R	TRUST\$1
1	<u>0.000</u>	<u>0.000</u>	<u>0.000</u>	<u>0.000</u>	<u>0.000</u>

	Residuals for Means/Intercepts/Thresholds				
	TRUST\$2	TRUST\$3	TRUST\$4	SKIP\$1	SKIP\$2
1	<u>0.000</u>	<u>0.000</u>	<u>0.000</u>	<u>0.000</u>	<u>0.000</u>

	Residuals for Means/Intercepts/Thresholds				
	SKIP\$3	SKIP\$4	GRAFFITI	GRAFFITI	GRAFFITI
1	<u>0.000</u>	<u>0.000</u>	<u>0.000</u>	<u>0.000</u>	<u>0.000</u>

	Residuals for Means/Intercepts/Thresholds				
	GRAFFITI	DISRESPE	DISRESPE	DISRESPE	DISRESPE
1	<u>0.000</u>	<u>0.000</u>	<u>0.000</u>	<u>0.000</u>	<u>0.000</u>

	Model Estimated Within Level Covariances				
	CLOSEKNI	ADULTS	HELP	ALONG_R	SAFE
CLOSEKNI	<u>1.000</u>				
ADULTS	0.393	<u>1.000</u>			
HELP	0.436	0.442	<u>1.000</u>		
ALONG_R	0.295	0.299	0.332	<u>1.000</u>	
SAFE	0.404	0.410	0.455	0.308	<u>1.000</u>
VALUES_R	0.166	0.168	0.187	0.126	0.173
TRUST	0.424	0.430	0.477	0.323	0.442
SKIP	0.283	0.287	0.319	0.216	0.295
GRAFFITI	0.301	0.305	0.338	0.229	0.314
DISRESPE	0.239	0.243	0.270	0.182	0.250

	Model Estimated Within Level Covariances				
	VALUES_R	TRUST	SKIP	GRAFFITI	DISRESPE
VALUES_R	<u>1.000</u>				
TRUST	0.181	<u>1.000</u>			
SKIP	0.121	0.310	<u>1.000</u>		
GRAFFITI	0.129	0.329	0.557	<u>1.000</u>	
DISRESPE	0.102	0.262	0.444	0.472	<u>1.000</u>

Residuals for Within Level Covariances

	CLOSEKNI	ADULTS	HELP	ALONG_R	SAFE
CLOSEKNI	0.000				
ADULTS	0.062	0.000			
HELP	0.016	0.032	0.000		
ALONG_R	-0.094	0.015	0.058	0.000	
SAFE	0.003	0.002	-0.011	-0.065	0.000
VALUES_R	0.028	-0.110	-0.050	0.209	-0.048
TRUST	-0.035	-0.033	0.039	0.006	-0.029
SKIP	-0.031	-0.130	-0.084	-0.046	0.106
GRAFFITI	-0.098	-0.032	-0.050	0.017	0.064
DISRESPE	0.051	-0.055	0.003	0.041	0.026

Residuals for Within Level Covariances

	VALUES_R	TRUST	SKIP	GRAFFITI	DISRESPE
VALUES_R	0.000				
TRUST	0.025	0.000			
SKIP	0.045	0.063	0.000		
GRAFFITI	0.024	0.020	0.024	0.000	
DISRESPE	0.011	0.034	-0.024	-0.013	0.000

Model Estimated Within Level Correlations

	CLOSEKNI	ADULTS	HELP	ALONG_R	SAFE
CLOSEKNI	1.000				
ADULTS	0.393	1.000			
HELP	0.436	0.442	1.000		
ALONG_R	0.295	0.299	0.332	1.000	
SAFE	0.404	0.410	0.455	0.308	1.000
VALUES_R	0.166	0.168	0.187	0.126	0.173
TRUST	0.424	0.430	0.477	0.323	0.442
SKIP	0.283	0.287	0.319	0.216	0.295
GRAFFITI	0.301	0.305	0.338	0.229	0.314
DISRESPE	0.239	0.243	0.270	0.182	0.250

Model Estimated Within Level Correlations

	VALUES_R	TRUST	SKIP	GRAFFITI	DISRESPE
VALUES_R	1.000				
TRUST	0.181	1.000			
SKIP	0.121	0.310	1.000		
GRAFFITI	0.129	0.329	0.557	1.000	
DISRESPE	0.102	0.262	0.444	0.472	1.000

It is important to inspect the correlation residuals for signs of misfit. Correlations with an absolute value of 0.1 or greater should be flagged, and model modifications should be considered (assuming these modifications are consistent with theory).

Residuals for Within Level Correlations

	CLOSEKNI	ADULTS	HELP	ALONG_R	SAFE
CLOSEKNI	0.000				
ADULTS	0.062	0.000			
HELP	0.016	0.032	0.000		
ALONG_R	-0.094	0.015	0.058	0.000	
SAFE	0.003	0.002	-0.011	-0.065	0.000
VALUES_R	0.028	-0.110	-0.050	0.209	-0.048
TRUST	-0.035	-0.033	0.039	0.006	-0.029
SKIP	-0.031	-0.130	-0.084	-0.046	0.106
GRAFFITI	-0.098	-0.032	-0.050	0.017	0.064
DISRESPE	0.051	-0.055	0.003	0.041	0.026

Residuals for Within Level Correlations

	VALUES_R	TRUST	SKIP	GRAFFITI	DISRESPE
VALUES_R	0.000				
TRUST	0.025	0.000			
SKIP	0.045	0.063	0.000		
GRAFFITI	0.024	0.020	0.024	0.000	
DISRESPE	0.011	0.034	-0.024	-0.013	0.000

Model Estimated Between Level Covariances

	CLOSEKNI	ADULTS	HELP	ALONG_R	SAFE
CLOSEKNI	0.137				
ADULTS	0.124	0.275			
HELP	0.113	0.170	0.211		
ALONG_R	0.110	0.166	0.152	0.216	
SAFE	0.073	0.110	0.100	0.098	0.097
VALUES_R	0.083	0.125	0.114	0.111	0.074
TRUST	0.150	0.226	0.206	0.202	0.134
SKIP	0.072	0.109	0.099	0.097	0.064
GRAFFITI	0.163	0.246	0.224	0.219	0.145
DISRESPE	0.032	0.048	0.044	0.043	0.028

Model Estimated Between Level Covariances

	VALUES_R	TRUST	SKIP	GRAFFITI	DISRESPE
VALUES_R	0.128				
TRUST	0.151	0.341			
SKIP	0.073	0.132	0.143		
GRAFFITI	0.164	0.298	0.144	0.376	
DISRESPE	0.032	0.058	0.028	0.063	0.099

Residuals for Between Level Covariances					
	CLOSEKNI	ADULTS	HELP	ALONG_R	SAFE
CLOSEKNI	0.000				
ADULTS	0.010	0.000			
HELP	-0.004	0.013	0.000		
ALONG_R	-0.017	-0.006	0.017	0.000	
SAFE	-0.005	-0.008	0.009	-0.002	0.000
VALUES_R	-0.012	-0.009	0.008	0.021	0.000
TRUST	0.001	-0.002	0.014	0.007	0.020
SKIP	0.022	-0.009	-0.031	-0.008	0.008
GRAFFITI	0.003	0.018	-0.018	0.011	-0.004
DISRESPE	0.026	0.007	0.012	-0.007	-0.010

Residuals for Between Level Covariances					
	VALUES_R	TRUST	SKIP	GRAFFITI	DISRESPE
VALUES_R	0.000				
TRUST	-0.001	0.000			
SKIP	0.007	-0.007	0.000		
GRAFFITI	-0.016	-0.007	0.033	0.000	
DISRESPE	0.010	-0.026	0.007	-0.017	0.000

Model Estimated Between Level Correlations					
	CLOSEKNI	ADULTS	HELP	ALONG_R	SAFE
CLOSEKNI	1.000				
ADULTS	0.638	1.000			
HELP	0.663	0.707	1.000		
ALONG_R	0.641	0.683	0.710	1.000	
SAFE	0.634	0.675	0.702	0.678	1.000
VALUES_R	0.624	0.665	0.691	0.668	0.661
TRUST	0.694	0.739	0.768	0.743	0.734
SKIP	0.516	0.550	0.572	0.552	0.546
GRAFFITI	0.719	0.765	0.796	0.769	0.761
DISRESPE	0.273	0.291	0.302	0.292	0.289

Model Estimated Between Level Correlations					
	VALUES_R	TRUST	SKIP	GRAFFITI	DISRESPE
VALUES_R	1.000				
TRUST	0.723	1.000			
SKIP	0.538	0.598	1.000		
GRAFFITI	0.749	0.832	0.619	1.000	
DISRESPE	0.285	0.316	0.235	0.328	1.000

It is important to inspect the correlation residuals for signs of misfit. Correlations with an absolute value of 0.1 or greater should be flagged, and model modifications should be considered (assuming these modifications are consistent with theory).

Residuals for Between Level Correlations

	CLOSEKNI	ADULTS	HELP	ALONG_R	SAFE
CLOSEKNI	0.000				
ADULTS	0.053	0.000			
HELP	-0.021	0.054	0.000		
ALONG_R	-0.101	-0.025	0.079	0.000	
SAFE	-0.042	-0.050	0.065	-0.011	0.000
VALUES_R	-0.088	-0.049	0.046	0.128	0.001
TRUST	0.004	-0.007	0.052	0.027	0.107
SKIP	0.154	-0.046	-0.180	-0.045	0.065
GRAFFITI	0.012	0.055	-0.063	0.040	-0.020
DISRESPE	0.225	0.041	0.081	-0.051	-0.107

Residuals for Between Level Correlations

	VALUES_R	TRUST	SKIP	GRAFFITI	DISRESPE
VALUES_R	0.000				
TRUST	-0.007	0.000			
SKIP	0.048	-0.033	0.000		
GRAFFITI	-0.071	-0.019	0.140	0.000	
DISRESPE	0.090	-0.141	0.057	-0.089	0.000

SAVEDATA INFORMATION

Within and between sample statistics with Weight matrix

Save file  
 cfa\_swmatrix.dat  
 Save format Free

DIAGRAM INFORMATION

Mplus diagrams are currently not available for multilevel analysis.  
 No diagram output was produced.

Beginning Time: 17:02:16  
 Ending Time: 17:03:40  
 Elapsed Time: 00:01:24

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