Latent Mean (Comparison)

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The comparison of means is one of the most central analyses in the social sciences. Most commonly, procedures such as *t*-tests, ANOVA, MANOVA, or growth curve modeling are conducted to investigate mean differences across populations or across time. This is appropriate if the means refer to an observed variable or if a factor analysis does not hold for the observed set of variables. However, if several variables refer to a common latent construct, it is more substantive to compare mean values within the structural equation modeling (SEM) approach. While communication research so far rarely applies latent mean modeling, especially comparative researchers should do so more frequently because the method is superior to comparing observed mean values in many respects. For instance, SEM can account for measurement error and considers different factor loadings when constructing a factor variable. The basic datum of SEM is the covariance matrix and usually only covariance structures are analyzed to test hypotheses. However, mean values of latent constructs can be estimated, too, by adding a mean structure to the data. This procedure is called structured means modeling (SMM). SMM facilitates a higher level of construct reliability and higher statistical power compared to procedures that rely on aggregated items only (Hancock, 2004; Steinmetz, 2010). An alternative approach to latent means modeling is Multiple-Indicator Multiple-Cause (MIMIC) models which do not even require a mean structure.

Advantages of latent means as compared to observed means

To illustrate the benefits of latent as compared to observed means, it helps to clarify how both methods relate to each other (see Steinmetz, 2010, pp. 86–88). Generally, the relationship between an observed variable x_i and a latent factor ξ in a common factor model can be described with the following equation:

$$x_i = \lambda_i \xi + \delta_i$$

The variance of the observed variable is partitioned into its factor loading λ_i and the unexplained variance or residual δ_i. This equation is the basis for the estimation of factor loadings, variances, and covariances of latent variables and measurement errors in confirmatory factor analysis (Steinmetz, 2010; Sörbom, 1974). In SEM, indicators are usually centered which implies means and intercepts are set to zero. The estimation

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of means makes it necessary to consider the metric of the original scale of indicators. Thus, the indicator intercept τ_i is added as a model parameter:

$$x_i = \tau_i + \lambda_i \xi + \delta_i$$

The intercept describes the difference between the observed value for x_i and the expected value that results from the product of the loading and the individual position on the latent mean dimension. From this, it is possible to derive the equation for the latent mean $M(\xi)$ and the observed mean $M(x_i)$:

$$M(x_i) = \tau_i + \lambda_i M(\xi) + M(\delta_i)$$

Since the distribution of errors has an expected value of zero ($M(\delta_i) = 0$), the equation can be simplified as follows:

$$M(x_i) = \tau_i + \lambda_i M(\xi)$$

The equation demonstrates that observed means are decomposed into intercepts, factor loadings, and latent means (Steinmetz, 2010, p. 88). The factor loading weighs the influence of each observed mean on the latent mean, while the intercepts scale the absolute level of the latent mean.

If procedures rely on observed variables, for example, mean indices, even though latent constructs are of interest, observed and latent means are simply equated. Thus, latent mean modeling is way more accurate and improves the validity of the analysis.

Structured means modeling

SMM (Sörbom, 1974) can be regarded as the classical approach towards comparing the latent means of different subsamples. As has already been explained, standard structural equation models are based merely on the covariance structure of the data. Therefore, they are only able to estimate factor loadings and regression coefficients. All means of latent variables are assumed to be zero. In order to determine mean differences between subgroups of a population on a latent variable, it is necessary to add a mean structure to the data, that is, to estimate intercepts and means. As a consequence, the input data for the model requires not only a covariance matrix but also a mean matrix.

The basic logic of modeling the mean structure within the multiple regression (MR) framework is as follows: In addition to a predictor and a dependent variable, a constant with the value of 1 is introduced into the model. When the dependent variable is regressed on the predictor and the constant, the unstandardized regression coefficient for the constant indicates the intercept of the regression equation. When the predictor is regressed on the constant as well, the unstandardized regression coefficient indicates the mean of the predictor (see Kline, 2011, pp. 299–302). This logic can be applied to a confirmatory factor analysis in which the endogenous latent factor ξ takes over the role of the predictor for multiple exogenous variables $x_{1, 2, \ldots, n}$ (see Figure 1). While the regression paths from the latent variable to the indicators indicate the respective factor

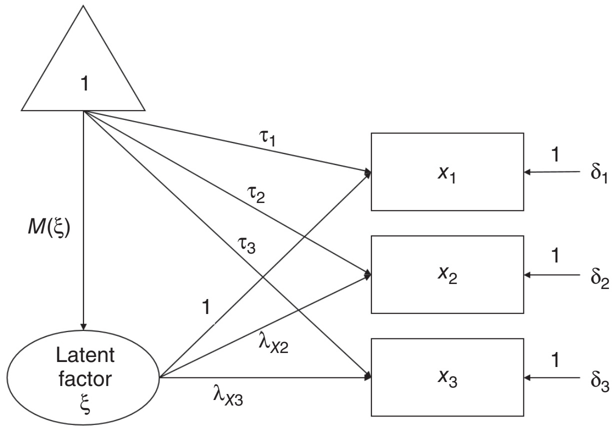

Figure 1 Basic logic of structured means modeling.

loadings $\lambda_{x1, x2, \ldots, xn}$, regression coefficients from the constant to the indicators represent their intercepts $\tau_{1, 2, \ldots, n}$. The coefficient for the regression of the latent variable on the constant is the latent mean of the factor $M(\xi)$.

However, the mean structure for the model shown in Figure 1 is underidentified: There are four parameters to be estimated (three indicator intercepts and one latent mean) but only three observations given (means of the three indicators). For a model with a latent mean structure to be identified it is therefore necessary to analyze the means for multiple groups (or points in time) in comparison to each other (Kline, 2011, p. 317). This is done by applying multigroup confirmatory factor analysis (MCFA; French & Finch, 2008), that is, dividing the dataset into at least two different subsamples.

For identification, it is also necessary to impose certain constraints on the model as has been suggested by Sörbom (1974): In the first step, the latent factor mean has to be fixed to zero in one group in order to establish a reference group. Factor values for additional groups are estimated freely. Their values can then be read as indicating the difference between the respective latent mean and the reference group's mean value. Moreover, it is also necessary to set the intercepts of the observed variables equal across groups.

Second, it has to be assured that the latent factors are constructed the same way in all groups. This is very important since latent mean comparison requires measurement invariance across groups (Schemer, Kühne, & Matthes, 2014). At the least, it is thus necessary to use the same scaling variable across all groups. This is the variable whose loading is fixed to 1 in order to identify the model. A more sophisticated and thus advisable option is to formally test for measurement invariance. This should be done before performing latent mean comparison. Hancock (2004, p. 328) generally recommends testing the fit of the covariance structure of any model before adding a mean structure. Model misfit at this first stage either indicates that the factor solution does not ideally match the data or that the ideal solution differs between groups. Only a well-fitting factor structure with measurement invariance across groups should be used to conduct latent mean comparison.

Table 1 Maximum likelihood parameter estimates for a one-factor model of political trust with structured means analyzed across samples from Norway and Italy.

	Norway			Italy		
Parameter	Unst.	*SE*	St.	Unst.	*SE*	St.
Factor loadings						
λ_{x1}: Trust in country's parliament	1.000	—	.738	1.000	—	.745
λ_{x2}: Trust in politicians	1.099	0.018	.924	1.099	0.018	.953
λ_{x3}: Trust in political parties	1.058	0.017	.894	1.058	0.017	.911
Measurement error variances						
δ_1	2.166	0.086	.455	2.789	0.140	.445
δ_2	0.536	0.045	.146	0.422	0.061	.091
δ_3	0.731	0.046	.201	0.800	0.065	.170
Indicator intercepts						
τ_1	6.218	0.052		6.218	0.052	
τ_2	5.125	0.047		5.125	0.047	
τ_3	5.134	0.047		5.134	0.047	
Factor mean						
$M(\xi)$	0			−2.917	0.085	

Note. Unst., unstandardized; St., standardized. $n_{\text{Norway}} = 1612$; $n_{\text{Italy}} = 956$. For all unstandardized estimates: $p \leq .001$. Model fit statistics: $\chi^2(4) = 40.063$, $p \leq .001$; CFI = .992; RMSEA = .084; SRMR = .050.

The simplest version of latent mean comparison narrows down to a model with two groups and one latent factor. An empirical example for such a model is shown in Table 1. It is based on data from the European Social Survey Round 6, which was conducted in 2012. The model was calculated using the software tool Mplus 7.3. It compares the latent means of the factor political trust for Norway and Italy. Political trust was measured using three items (e.g., "On a score of 0–10 how much [do] you personally trust […] political parties?"). Results indicate that the average level of trust in political institutions is 2.917 scale points lower in Italy than in Norway on the 11-point scale from 0 (= no trust at all) to 10 (= complete trust) which was used for the three items. Model fit statistics are only just acceptable though which indicates that there might not be perfect measurement invariance between the two countries.

Latent mean comparison can be conducted for more complex data as well. Samples can be divided into more than two groups and a model structure can be added, for example, by introducing a latent covariate to the model (for an overview of possible model extensions, see Hancock, 2004, pp. 330–331). Moreover, it is also possible to calculate effect sizes of latent mean differences and to conduct post hoc tests to determine significantly different latent mean values (for an overview, see Hancock, 2001).

MIMIC models as an alternative approach

An alternative approach to comparing group differences concerning a latent variable is to calculate a MIMIC model (Muthén, 1989). This approach can be regarded as the

SEM equivalent to testing the effect of group membership on a dependent variable with one or more independent dummy variables in a regression model (Hancock, 2004, pp. 324–325). Unlike the *t*-test approaches, this method does not operate with the comparison of mean values for different subsamples but uses data from all groups within the same sample. Instead, the dataset contains *j*−1 dummy variables for *j* different groups that clearly assign each case to one of the groups. These dummy variables are then used as predictors for the dependent variable in the regression model. Estimated regression coefficients inform about group differences concerning the dependent variable. Although leading to similar results as *t*-test approaches, this method does not operate with actual variable means.

The same is true for the MIMIC modeling approach in SEM. Group differences on a latent variable can be tested with a MIMIC model based merely on the covariance structure. The model does not require a mean structure and ignores all intercepts. The dataset for a MIMIC model is not partitioned into different subsamples but should contain *j*−1 dichotomous dummy variables for *j* different groups. The latent construct is regressed on one or more dummy variables in order to determine group differences. As in the regression approach for observed dependent variables, estimated regression coefficients inform about the effect of group membership on the latent score. More specifically, the unstandardized coefficient for the path from the dummy variable to the latent construct can be read as indicating the latent mean difference in scale points between the respective group and the reference group. Moreover, it is impossible to test for measurement invariance within the MIMIC modeling framework. Just as for SMM models, MIMIC models are based upon the assumption that measurement invariance is given between groups. However, they are not able to test this assumption—which is a clear disadvantage in comparison to SMM (Kline, 2011, p. 323).

Figure 2 shows an example of a MIMIC model for two groups. It is based upon the same data as the SMM model presented in Table 1 and has also been calculated with Mplus 7.3. Group membership is represented in the country dummy variable. Again, more complex MIMIC models may contain more than two groups and thus also more than one dummy variable. They can also include observed or latent covariates which the exogenous latent factor is then regressed on as well (Hancock, 2004, p. 324).

Recommendations for (comparative) communication research

Most empirical research in the social sciences deals with latent constructs. So does communication research. Individuals' attitudes, opinions, and emotions, but also latent message patterns within media content cannot be directly measured with one observed indicator but have to be assessed by approximation through a set of indicator variables. For combining these indicator variables in one construct, the SEM framework is way superior to classical statistical approaches since it accounts for measurement error and a differently strong contribution of the indicator variables to the latent construct under consideration. That is why SEM has become very popular among communication researchers over the last two decades.

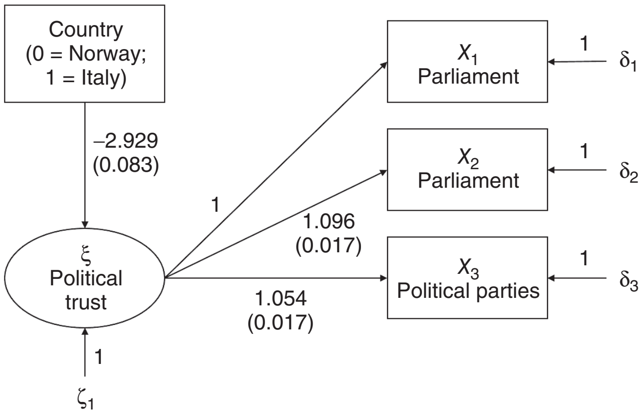

Figure 2 Maximum likelihood parameter estimates for a one-factor MIMIC model of political trust.
Note. Values are unstandardized estimates with standard errors in parentheses. $n_{\text{Norway}} = 1{,}612$; $n_{\text{Italy}} = 956$. For all estimates: $p \leq .001$. Model fit statistics: $\chi^2(2) = 30.879$, $p \leq .001$; CFI = .996; RMSEA = .075; SRMR = .010.

However, despite its superiority over classical approaches of mean comparison, the application of latent mean comparison can still rarely be found. Communication scholars should make more use of this method, especially if their research is interested in comparing the levels of a latent construct between different groups. Possible fields of application are internationally comparative research, research that assesses longitudinal developments, but also experimental studies where a manipulation is deemed to affect one or more latent outcome variables. For these kinds of questions, latent mean comparison is the most appropriate statistical approach. It leads to a more precise and fine-grained analysis than working with index variables. Communication researchers should thus set out to apply latent mean comparison on a regular basis. More specifically, it is advisable to follow the SMM rather than the MIMIC approach since it helps to detect possible measurement variances between comparison groups.

SEE ALSO: Amos (Software); Analysis of Covariance; Factor Analysis, Confirmatory; Latent Growth Curve Modeling; Measurement Invariance (Time, Samples, Contexts); Structural Equation Modeling

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