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Meta-analytical Structural Equation Modelling

Potentials and Limitations Illustrated with an Example from Organizational Psychology

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Abstract: Meta-analyses are an important part of the methodological inventory for the synthesis of empirical findings and the derivation of evidence-based measures. So far, univariate approaches have dominated, which aim at the integration and analysis of individual effect sizes and are, thus, of limited value for testing multivariate (causal) relationships. Meta-analytical structural equation models (MASEM) represent a helpful extension, as they allow a meta-analytical analysis of complex multivariate structures. In addition, MASEM can be used to map dependencies between multivariate effect sizes and multi-level structures. The aim of this paper is to outline the conceptual foundations of MASEM and to illustrate them using an empirical example from organizational psychology. Finally, a critical discussion of the limitations of the approach will be provided.

Keywords: meta-analyses, research synthesis, structural equation models, MASEM

Meta-analyses are a valuable alternative to narrative reviews and ideally offer an objective and standardized overview of the research on a given issue. They are considered not only as an important tool of theory-based research, but also as an important basis for evidence-based practice. However, while meta-analyses of experimental studies mainly focus on heterogeneity, i.e. significant differences in effect sizes and estimation of a mean causal effect (Smith & Glass, 1977), meta-analyses in non-experimental fields are based on an aggregation of bivariate correlations.

Even though these 'univariate approaches' have established themselves in the literature as a helpful form of synthesis of research, the combination of meta-analysis and meta-analytical structural equation modeling (MASEM) represents a decisive expansion of the meta-analytical spectrum of methods. Analogous to the application of structural equation models on primary data, a MASEM is based on the correlation matrix of several features. The difference to a primary study is that each cell of this matrix is formed meta-analytically. The specified model then represents a summary of all hypothetical causal effects of the variables and allows to test the implications resulting from the model by means of statistical tests and other evaluation standards (Kline, 2016). Although even a good model fit with the data does not prove the correctness of the causal assumptions, it is at least a possibility to test causal hypotheses.

In particular, MASEM offers the following advantages (compared to univariate approaches): First, more complex causal structures can be specified and thus multivariate models and theories can be represented in their breadth (Brown & Peterson, 1993). In this case, the results of the models represent a compact and integrated form of evidence of or against the theory. Second, MASEM allows the comparison of competing models or theories that entail different implications for the data (Harrison, Newman & Roth, 2006; Hom, Caranikas-Walker, Prussia & Griffeth, 1992). For example, Hom et al (1992) compare different process models of the development of an intention to quit a job by means of meta-analytical models.

Third, MASEM enables the analysis and testing of mediators as postulated central processes underlying an effect (Shadish, 1996). Mediators are of enormous importance, both theoretically and practically, because they can answer the theoretical question of 'why' of an effect as well as the practically relevant question about potential mechanisms. A model can involve several mediators simultaneously and is much more flexible in taking into account the complexity of mediator structures (e.g. by estimation of effects of mediators on each other). This is particularly essential if there are several mediators with opposite signs, thus, attenuating or even eliminating an overall relationship. One example is Murayama and Elliot's MASEM (2012) on the impact of competitive situations in individual performance contexts, in which the authors show that while there is no substantial general relationship between competition and performance, there are two mechanisms that have opposite signs.

Fourth, a multivariate model implies that effects of variables are estimated while keeping other variables statistically constant. Thus, it is possible to explicitly include control variables in MASEM, even if this usually results in practical limitations due to the limited availability of a sufficient number of studies. Fifth, it is possible to integrate variables into a model that make it possible to reduce the plausibility of alternative causal directions or non-considered confounding variables. Such instrumental variables have become essential in fields such as econometrics for decades, and are slowly emering in psychology (Antonakis, Bendahan, Jacquart & Lalive, 2010) and in the analysis of structural equation models (Maydeu-Olivares, Shi & Rosseel, 2019; Steinmetz, 2014). This approach is also attractive because model structures often exist in which instrumental variables are already an integral part of the tested model.

Overall, MASEM thus represents a powerful approach to combine the advantages of meta-analyses (e.g. systematic aggregation of respective research papers, large samples, and possibilities to analyze differences between studies) with those of structural equation models.

Approaches and procedure

In contrast to classical univariate meta-analyses based on the approaches of Hedges and Olkin (1985) and Schmidt and Hunter (2015), a MASEM is based on a meta-analytically formed correlation matrix of all model variables. Three methods have been developed so far to generate this correlation matrix (Sheng, Kong, Cortina, & Hou, 2016).

The "pairwise aggregation approach" (Brown & Peterson, 1993; Viswesvaran & Ones, 1995) consists in forming the individual cells of the pooled correlation matrix by means of univariate meta-analyses isolated from each other. The correlations are also isolated and tested for heterogeneity, as is usual with univariate meta-analyses. In the following step, the correlation matrix thus generated is then used as the basis for the specification and testing of the model.

The "two-step approach" (Cheung & Chan, 2005b) is based on a critique of the pairwise aggregation approach, for instance, the isolated heterogeneity tests, the unclear sample size with a different number of correlations per cell and the inadequate use of a (standardized) correlation matrix as the basis for a model. In contrast, the alternative of Cheung and Chan (2005b) proposes aggregating the correlation matrices in the first step by using a multi-group model in which each primary study is treated as a separate "group". The result is an estimate of the total correlation matrix across all studies and cells of the matrix. In the second step, the total matrix estimated in this way is used as the basis for the MASEM. Information about differences between the groups in the correlations and sample sizes from the first step is used to weight individual parameters of the model. Consequently, parameters of the model that are based on studies with small sample sizes will result in larger uncertainties (in terms of confidence intervals).

The third, multi-level based, approach (Wilson, Polan & Lipsey, 2016) addresses the problem in meta-analyses that primary studies often contain multiple, statistically dependent effect sizes (Cheung, 2014; Steinmetz, Knappstein, Ajzen, Schmidt & Kabst, 2016). For example, the meta-analysis of Steinmetz et al. (2016) included primary studies that compared several treatment groups with the same control group. Similarly, it often happens that several correlations are presented in a primary study, all of which represent the same target correlation relevant for the meta-analysis. Since the multiple effect sizes reported in one study are more similar to each other than if they came from different studies, variances in effect sizes are underestimated. Multi-level meta-analyses are comparable with conventional multi-level analyses, in which, for example, people are nested in teams. While a simple regression model would assume the independence of the persons, a multi-level analysis allows it to consider the stronger similarity of the persons in the team. Likewise, the multi-level meta-analysis considers the similarity of effect sizes by considering the specific effect sizes as nested in studies and statistically taking this structure into account.

While the original applications of multilevel meta-analysis were aimed at univariate effect sizes, Wilson et al. extended the approach to MASEM, entails performing a multi-level random-effects regression in the first step, in which a single vector with all available correlations is regressed on a set of dummy variables that merely represent the names of the individual correlations in the vector in question. Table 1 shows an exemplary section of the data set on which this regression is based. Of particular relevance here are the column with the study identification number, each of which refers to a sample under investigation, and the columns with the correlations and the corresponding naming variables. Since the latter is treated as categorical in the regression analysis and the regression model is calculated without an intercept, the regression coefficients reflect the weighted mean correlations per cell of the matrices, which is represented by the name of the respective correlation. Overall, the regression analysis thus provides all aggregated correlations of the matrix in a single step. As in the approach of Cheung and Chan (2005b), this correlation matrix is then used as the basis for the MASEM; information on differences between the studies is used to weight the parameters and the sum of the sample sizes is used as the relevant sample size.

Overall, the multi-level approach has several advantages over the two-step approach. First, multiple correlations are the rule rather than the exception in practice, especially if the target constructs are located at a higher level of abstraction. The multi-level approach then allows the correlations presented in the primary studies to be meta-analyzed in the form in which they exist without having to take the detour criticized in the literature of forming intra-study averages (Cheung, 2014). The practical advantages include the fact that the correlations of the primary studies are directly transferred and any manipulation (e.g. by the aforementioned averaging, aggregation, or renaming) is avoided. Thus, the meta-analytical data set exactly represents the content of the primary studies, which increases transparency and replicability. Theoretical and methodological decisions (e.g. on the selected level of abstraction) are made by the above-mentioned naming of the correlations and can be flexibly adapted for alternative levels of aggregation or future studies. A disadvantage of the approach is that the correlation matrix generated in the first step is directly used as a basis for the model, which is actually based on a covariance matrix. This is where Cheung's approach is advantageous, in that a potentially distorting effect is avoided by an elegant use of the group model.

Illustration of the MASEM approach

The model

Due to the advantages of the multi-level approach, we have chosen it for illustration purposes, even though the problem of multiple correlations did not exist in the given case. The starting point is a model that tests the effect of team diversity in working groups on conflicts, cohesion, and team performance. The focus of interest here is, on the one hand, bio-demographic diversity, which refers to easily identifiable characteristics such as gender, age, or ethnicity, and, on the other hand, task-related diversity, as is the case with differences in the functional areas or educational paths of team members (Horwitz & Horwitz, 2007).

The specified model (see Fig. 1) proposes that bio-demographic diversity leads to a greater degree of relationship conflicts due to the categorization processes predicted by social identity theory (Tajfel, 1982). In contrast, task-related diversity should lead to stronger task-related conflicts. Since these may escalate, an additional effect on relationship conflicts is assumed. Finally, the model postulates that the effect of both types of relationship on team performance is entirely mediated by the cohesion of the team. The model structure is well suited to illustrate the discussed advantages of a multivariate approach over the univariate focus on individual correlations: There are correlating predictors whose influence must be mutually controlled as well as mediators with potentially opposing effects. Finally, the structure provides for an isolated influence of both diversity characteristics on specific forms of conflict, which gives them the status of potential instrumental variables and allows to test the downstream parts of the model for confounding factors or reverse effects and, in a given case, to estimate the effects, despite their presence, consistently.

Data and modeling procedure

The data basis is formed by a total of 52 publications, which had provided correlations from one sample each ($N = 3,383$ teams) and reported a total of 211 correlations. The studies varied greatly with regard to the number of correlations reported: For example, 28 studies reported a correlation between task-related diversity and team performance, but only 3 studies reported a correlation between relationship conflicts and cohesion.

In a first step, the meta-analytical aggregation of the correlation matrices was performed by means of a random effects dummy regression (Wilson et al., 2016). The metafor package (Viechtbauer, 2010) within the software package R was used for this purpose (R Core Team, 2019). Instead of the symmetrical matrix, Table 2 shows the output of the regression. Each row represents an expression of the categorical variable that was used to name each correlation, and the regression weights are the meta-analytical averaged correlations. In a second step, the structural model was specified and estimated using the metaSEM package (Cheung, 2015).

The fit of the tested model did not point to a misfit ($\chi2$ (df) = 15.3 (8), $p = .05$, RMSEA = .02). The parameter estimates (see Fig. 1) did show non-significant effects for bio-demographic diversity and marginal effects for task-related diversity. In contrast, the effects of both conflict types on cohesion and of cohesion on team performance were substantial and significant. However, the results show effects of both conflict types that are mediated by cohesion. Assuming the correctness of the specified structure, this would imply two effects on cohesion and performance especially for task-related conflicts - a positive direct effect via positive stimulation of team discussions, but also a negative indirect effect via the higher probability of harmful relationship conflicts. MASEM thus makes a valuable contribution to decomposing general relationships into partial effects.

While usual representations of structural equation models usually end with the presentation of parameter estimates, more detailed discussions can be held on the basis of graph-theoretical principles (Pearl, Glymour & Jewell, 2016) to evaluate to what extent the model or certain parts of it support the underlying causal assumptions. In this regard, the possibility of equivalent structures with the same implications for the data plays a central role (Spirtes, Glymour & Scheines, 2003). This enables a more informative and differentiated assessment of the evidence by the model. While the basic structure of the model provided a very good starting point for causal interpretations specifically for the effects of conflict and cohesion, the non-significant effects of diversity variables led to the cancellation of their instrumental variable function for these effects (Antonakis, et al., 2010). As a result, the relationships between the two types of conflict and cohesion could not be tested for confounding or reversibility effects. The interpretation of the coefficients is thus based on the theoretical plausibility of assumptions about the effects of the conflicts (versus alternatives).

The effect of cohesion on team performance, on the other hand, is on a somewhat more solid ground, although an alternative model with a completely reversed causal direction (team performance → cohesion → conflicts) or even a purely spurious correlation between cohesion and performance cannot be distinguished from the tested model. Here, concrete theoretical assessments are required to determine the extent to which specification errors of such magnitude are plausible. To evaluate this critically could be the central implication of this MASEM for future research.

Heterogeneity

As in any meta-analysis, heterogeneity plays an important role in a MASEM and is even more significant than in meta-analyses with bivariate correlations: Like any structural equation model, a MASEM is based on the assumption of causal homogeneity (Mulaik, 2009; Muthén, 1989), which means that it describes a population in which there are no subgroups with different effects (Mulaik, 2009, p. 188). In the case of causal heterogeneity, a potential bias depends on the number of subpopulations as well as the extent and nature of the differences across subpopulations. In the case of moderate heterogeneity, where only the strength of the effects varies across groups, effect estimates can simply be interpreted as mean effects (see the discussion of a relevant exception in Winship & Elwert, 2010). In extreme cases, however, completely different causal structures are present, which make aggregation meaningless.

For these reasons, the analysis of heterogeneity is of great importance. First of all, an important indication is the model fit: While an empirically insufficiently fitting model can of course indicate a general mis-specification, the mismatch can also be determined by causal heterogeneity. For example, the aggregation of subgroups with different structures leads both to distorted mean effects and to a mismatch of the model to the data. Traditionally, the observed heterogeneity of the correlation matrix, but also of individual, theoretically relevant correlations, is another indicator.

In both cases, an attempt should be made in a MASEM application to identify moderators who can explain the heterogeneity. Due to the multivariate data structure, this is more difficult than in the case of simple correlations. Suggestions range from the possibility of performing a subgroup analysis to categories of individual observed moderators (Jak & Cheung, 2018) and the use of cluster analyses (Cheung & Chan, 2005a) to identify groups with similar profiles of correlations. Disadvantages are difficulties in interpreting the identified groups (Steinmetz, Isidor, & Baeuerle, 2012).

Wilson et al (2016) present an interesting approach to use the weights of the moderators estimated in a meta-regression analysis to predict a correlation matrix that would correspond to a desired profile of moderators and to use this as the basis for the model. For example, a moderator "task complexity" weight estimated in the meta-regression of B = .5 for the correlation between task-related conflicts and team performance would allow this correlation to be predicted for a desired value of this moderator (e.g., estimated role of task-related conflicts for highly complex professions). Applied to all the moderators studied and the entire correlation matrix, this allows the prediction of the entire matrix for a desired profile of moderator - for example, for teams with the profiles "technology sector", "high task complexity" and "from individualized cultures".

While the most intuitive and easy-to-interpret approach is subgroup analysis, in most cases this fails due to incompletely occupied cells of the correlation matrix as a consequence of group separation. In these cases it will therefore only be possible to perform traditional moderator analyses with central bivariate correlations. Results may alert future research to potential moderators of the underlying effects. In the current study, for example, specific homogeneity tests showed that correlations between biodemographic diversity and relevant variables were homogeneous, while correlations between task-related diversity and relevant variables (e.g. team performance) deviated significantly from the homogeneity assumption. The latter could provide a basis for moderator analyses of the correlations in question, although they would still have to focus on the bivariate correlation.

Conclusion and limitations

Compared to univariate meta-analyses, MASEM offers the advantages of modeling complex theories, inclusion of control variables, estimation of indirect effects and a model test. However, in practice they are often subject to restrictions, especially in the availability of variables whose inclusion would be theoretically useful or (e.g. as control variables) necessary. In addition, the 'apple-and-pear problem' of aggregating the most diverse constructs (Lipsey & Wilson, 2001), which is frequently discussed in the meta-analytical literature, has special implications, since the risk of causal heterogeneity increases with a broad focus of the meta-analysis. On the other hand, a more specific focus leads to a reduction in the empirical basis and thus the number of available studies and possible variables. Finding a reasonable compromise here is a central task of every MASEM approach.

Overall, MASEM makes a significant contribution to research synthesis and represents an improvement over univariate approaches; however, they do not replace strict primary studies, which offer better opportunities for strengthening internal validity. Instead, MASEM tries to combine both the addressing of classical questions of generalizability and causal identification in a useful way and can serve as a starting point for a targeted implementation of future primary studies.

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Table 1: Example excerpt from the data set

Study ID	Effect size ID	Name of the correlation	r
1	1	Task-based diversity - Bio-demographic diversity	.22
1	2	Cohesion - Bio-demographic diversity	.36
1	3	Relationship Conflicts - Bio-demographic Diversity	- .23
1	4	Task-related conflicts - Bio-demographic diversity	-.07
2	5	Team Performance - Bio-demographic Diversity	-.18
2	6	Cohesion - Task-based diversity	.24
2	7	Relationship Conflicts - Task-based Diversity	-.46
3	8	Task-related conflicts - Task-related diversity	.32
4	9	Team Performance - Task-Based Diversity	-.23
4	10	Relationship Conflicts - Cohesion	-.36
5	11	Task Conflicts - Cohesion	.24
5	12	Team Performance - Cohesion	.16
5	13	Task Conflicts - Relationship Conflicts	- .69
6	14	Team Performance - Relationship Conflicts	- .23
6	15	Team Performance - Task Conflicts - Task Conflicts	-.18
6	16	Cohesion - Bio-demographic diversity	-.12
6	17	Cohesion - Bio-demographic diversity	.03
6	18	Team performance - Bio-demographic diversity	-.03
6	19	Team performance - Cohesion	.32
7	20	Cohesion - Bio-demographic diversity	-.17
7	21	Team performance - Bio-demographic diversity	.35
7	22	Team performance - cohesion	.39
8	23	Cohesion - Task-based diversity	.10
8	24	Team Performance - Task-based Diversity	.08
8	25	Team Performance - Cohesion	.05
9	26	Cohesion - Task-based diversity	.06
9	27	Team Performance - Task-based Diversity	.20
9	28	Team Performance - Cohesion	.32
10	29	Cohesion - Task-based diversity	.06
10	30	Team Performance - Task-based Diversity	.03
10	31	Team Performance - Cohesion	.18
11	32	Team Performance - Task-based Diversity	.04
12	33	Team Performance - Task-based Diversity	.38
13	34	Task-based Diversity - Bio-demographic Diversity	- .26

Table 2: Result of the random effects dummy regression

Correlation	B (SE)	CI (95%)	
Task-based diversity - Bio-demographic diversity	.10 (.05)	.00	.20
Task-based diversity - Task-based diversity	.14 (.06)*	.02	.26
Task-related Conflicts - Relationship Conflicts	.47 (.04)**	.39	.56
Task-based Conflicts - Bio-demographic Diversity	.05 (.06)	-.06	.16
Task-based conflicts - Cohesion	.09 (.12)	-.15	.33
Relationship Conflicts - Task-based Diversity	.02 (.07)	-.10	.15
Relationship Conflicts - Bio-demographic Diversity	.07 (.05)	-.03	.17
Relationship conflicts – cohesion	- .20 (.12)	-.43	.04
Team performance - Task-based diversity	.07 (.04)	-.01	.14
Team performance - Task related conflicts	-.09 (.05)	-.19	.02
Team performance - Relationship conflicts	-.18 (.06)**	-.29	.08
Team performance - bio-demographic diversity	.01 (.04)	-.07	.09
Team performance - Cohesion	.26 (.06)**	.15	.37
Cohesion - Task-based diversity	.00 (.07)	-.13	.13
Cohesion - Bio-demographic diversity	.03 (.08)	- .13	.19

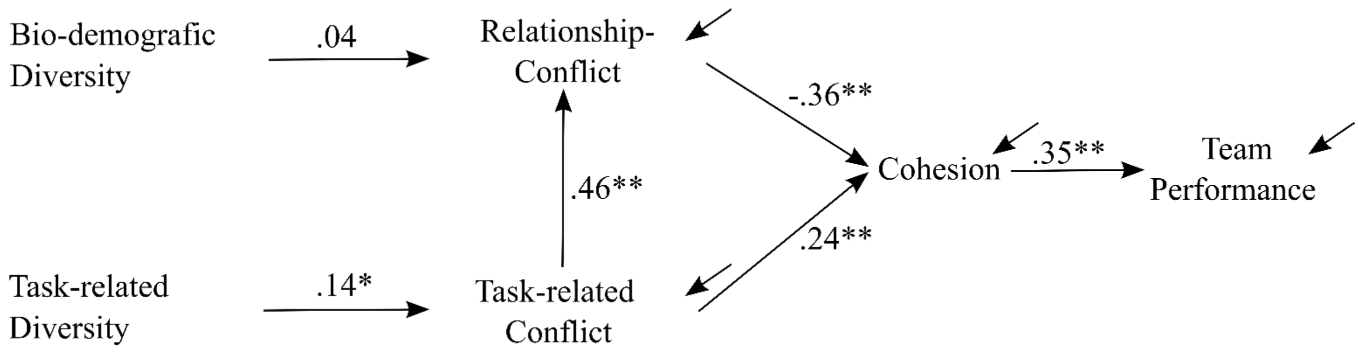

Figure 1: Tested model