Editorial

Still Comparing Apples With Oranges?

Some Thoughts on the Principles and Practices of Measurement Invariance Testing

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Measurement invariance testing has become an integral part of the methodological repertoire in psychological assessment. Whenever researchers attempt to compare scales or test scores across groups or over time, it needs to be ensured that they do not compare “apples with oranges.” Measurement invariance testing is the road that leads to the information about whether the comparisons of means or variances are valid. In other words, invariance testing examines the between-group or between-time points variation in factor means and variances by ruling out differences in measurement (Bauer, 2017). This ensures the fairness of scales or tests and therefore contributes to crafting a validity argument (Kane, 2013).

In this editorial, we briefly review some of the principles and practices of measurement invariance testing in psychological assessment contexts and encourage *EJPA* authors to critically review the limitations of the commonly used approach to invariance testing – multi-group confirmatory factor analysis. We suggest considering alternatives to this approach, for instance, when submitting to *EJPA* and we discuss the potential of these alternative approaches.

Same Procedure as Every Time: Multi-Group Confirmatory Factor Analysis

Measurement invariance across groups or over time is commonly tested by means of multi-group confirmatory factor analysis (CFA) – a procedure that compares factor models with different sets of equality constraints on parameters (Meredith, 1993). Indeed, our review of *EJPA* papers that performed measurement invariance testing showed that

multi-group CFA was the method of choice in more than 70% of the studies (publication period: January 1995–August 2017; for details, please refer to the Electronic Supplementary Material, ESM 1). Typically, once it has been established that the overall setup of a measurement model is comparable across groups or over time (configural invariance), equality constraints of the factor loadings, item intercepts, and residual variances are introduced, leading up to metric, scalar, and strict invariance. However, the list of available parameter constraints and combinations thereof can be extended in order to meet other levels of invariance (see, for example, Marsh et al., 2009).

To identify which level of invariance is met, multi-group models with different constraints are compared against each other by means of chi-square difference testing or by evaluating differences in fit indices, such as the CFI, RMSEA, or SRMR, against suggested cut-offs. At this point, we would like to emphasize that these cut-offs must not be considered “golden rules” (see also Greiff & Heene, 2017) – they do not generalize to all contexts (e.g., data structures and types) and thus require a critical evaluation of the contexts in which they are applied. Among others, these cut-offs depend on the treatment of item responses (i.e., continuous vs. categorical), the number of factors, the type of measurement model (e.g., correlated-factors vs. nested-factor models), the number of groups or time points, and the level of invariance that is tested (e.g., Khojasteh & Lo, 2015; Rutkowski & Svetina, 2014). Besides the issues related to the sensitivity of model fit indices toward detecting measurement invariance, multi-group CFA bears a number of other limitations with regard to factor structure and the scale of the grouping variable, which has to be discrete. For complex psychological measures, however, more complex factor structures may occur; in addition, in some research contexts, invariance across continuous rather than

categorical variables (e.g., age) is of interest. In the following, we will bring to attention alternatives to multi-group CFA that address these issues.

And Yes, There Is More: Procedures Beyond Multi-Group CFA

Researchers often find themselves in situations where the desired level of measurement invariance, especially scalar invariance to compare factor means across groups, is not achieved by means of multi-group CFA. Marsh et al. (2017) even argue that some levels of invariance are “an unachievable ideal that in practice can only be approximated” (p. 1). Hence, the question is: What are the options researchers have if measurement invariance testing by multi-group CFA fails or if they want to explore other options in general?

Non-Invariance Is a Finding

We consider evidence against invariance a relevant finding, especially when presenting newly developed measures or well-established measures that have been studied in new contexts or for new samples without establishing measurement invariance. Knowledge on non-invariance can aid the creation of a validity argument and informs test developers and researchers about the functioning of the scale or test (Kane, 2013). In this sense, we encourage *EJPA* authors to not shy away from reporting negative results concerning the invariance of certain measures. However, we also encourage authors to take the evaluation of invariance a step further, either by discussing possible reasons for departures from measurement invariance and the consequences for the interpretation of the scale or test scores or by identifying statistically the items or subsets of items that function differently across groups or over time. To accomplish the latter, existing approaches to differential item functioning (DIF), such as the multiple indicators multiple causes (MIMIC) models or models based on item response theory, are particularly helpful and can supplement the findings obtained from multi-group CFA (e.g., Hatlevik, Scherer, & Christophersen, 2017; Woods, 2009). Alternatively, authors may relax some of the parameter constraints in multi-group CFA invariance models and thus establish levels of partial measurement invariance. Reporting partial invariance, however, needs a thorough documentation of the steps authors have taken to arrive at these levels and might be less preferable for *EJPA*.

Alternatives to Multi-Group CFA

Over the last decade, several approaches to measurement invariance testing have been presented in the psychometric

literature, some of which address the limitations of multi-group CFA directly and thus provide viable alternatives to the standard approach. Table 1 shows a selection of these approaches.

In some instances, the factor structure of a scale or test is best represented by complex rather than simple structures. In other words, more than one factor may explain variation in the responses to one item. Besides nested factor models, exploratory structural equation models provide viable alternatives to CFA that account for these aberrancies from simple structures. Marsh et al. (2009) extended the exploratory SEM framework to multi-group models for which measurement invariance can be tested directly. Another class of models that accounts for possible cross-loadings in factor structures refers to Bayesian structural equation models. Bayesian SEM uses priors and prior distributions of parameters in factor models rather than point estimates – a feature that allows including cross-loadings in multi-group models. Besides, instead of establishing exact invariance, approximate invariance can be established based on approximate equality constraints of model parameters across groups or over time (Van De Schoot et al., 2013).

Another issue that often leads to non-invariance based on multi-group CFA concerns the number of groups or time points for which invariance is tested – the more groups or time points, the less likely it is to find higher levels of invariance, especially scalar invariance (Marsh et al., 2017). Recently, two approaches to invariance across many groups have received attention: the alignment method and multi-level factor analysis (Muthén & Asparouhov, 2017). The former estimates group-specific factor means and variances to approximate scalar invariance. The latter quantifies between-group variation in model parameters (e.g., factor loadings, item intercepts) using random effects and allows researchers to detect possible sources of non-invariance (Kim, Cao, Wang, & Nguyen, 2017).

In some instances, researchers may want to test measurement invariance across originally continuous variables, such as age or socioeconomic status. Instead of arbitrarily categorizing these variables for multi-group CFA, researchers may well treat them continuously and perform a more direct and flexible invariance testing procedure – moderated factor analysis (Bauer, 2017). This procedure describes variation in model parameters (e.g., factor loadings, item intercepts, factor means and variances) as a function of continuous and/or categorical variables.

Besides, even more sophisticated approaches exist and researchers should make use of them. Brandmaier, von Oertzen, McArdle, and Lindenberger (2013) presented structural equation modeling trees – a data-mining procedure that identifies previously unobserved groups in the data set for which parameters in a structural equation model differ. Kim et al. (2017) argued that factor mixture

Table 1. Selected measurement invariance testing procedures in multi-group settings

Procedure	Description	Grouping variable	References
Multi-group CFA	Testing a series of equality constraints on parameters in measurement models that have a simple or nested structure across groups	Categorical	Pendergast, von der Embse, Kilgus, and Eklund (2017)
Multi-group Exploratory SEM	Testing a series of equality constraints on parameters in measurement models that have a complex structure across groups	Categorical	Marsh, Morin, Parker, and Kaur (2014)
Multi-group Bayesian SEM	Testing the sensitivity of approximate equality constraints on model parameters across groups	Categorical	Van De Schoot et al. (2013)
Alignment method	Estimation of group-specific factor means and variances to approximate scalar invariance	Categorical	Marsh et al. (2017); Muthén and Asparouhov (2017)
Multilevel factor analysis	Testing a series of equality constraints on parameters in measurement models across groups – the grouping variable is considered random	Categorical	Muthén and Asparouhov (2017)
Moderated factor analysis	Testing moderation effects of grouping variables and/or covariates on item parameters (i.e., tests for differential item functioning)	Categorical and/or continuous	Bauer (2017)

Note. CFA = Confirmatory factor analysis, SEM = Structural equation modeling.

models may also be used to identify unobserved groups under certain invariance constraints. Finally, Hildebrandt, Lüdtke, Robitzsch, Sommer, and Wilhelm (2016) proposed locally weighted structural equation modeling to examine measurement invariance across continuous variables (e.g., age), next to moderated factor analysis.

Conclusion

Overall, this editorial sought to encourage *EJPA* authors to take a critical approach to the use of multi-group CFA for invariance testing. We would like to highlight three aspects surrounding the principles and practices of invariance testing via multi-group CFA: First, the application of model fit criteria to compare nested invariance models should always be evaluated considering the complexity of measurement models, the study sample, and the treatment of data – the standard model fit criteria do not represent “golden rules”. Second, standard invariance testing procedures, including multi-group CFA, have certain limitations – we therefore encourage authors to consider alternative, perhaps more suitable approaches to modeling their data. Third, we believe that the analysis of differential item functioning provides more specific information about whether certain items in a scale or test are invariant across groups or over time. This procedure can supplement more global tests of measurement invariance and thus strengthen the creation of a validity argument.

Electronic Supplementary Material

We have put together a supplementary material that provides a systematic overview of the current practices of measurement invariance testing employed in *EJPA* publications. We believe that this material provides a valuable source for authors who would like to (a) examine whether evidence for the invariance of certain scales has been reported in *EJPA* papers, and (b) explore the diversity of invariance testing approaches.

The electronic supplementary material is available with the online version of the article at <https://doi.org/10.1027/1015-5759/a000487>

ESM 1. Tables (.xlsx)

Systematic review of empirical *EJPA* papers performing measurement invariance texts.

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