PRACTICAL PROBLEMS OF THE SEM APPLICATION IN SOCIAL SCIENCES – REPORTING RESEARCH RESULTS*

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ABSTRACT

In this paper we present problems in reporting the results of structural equation modeling (SEM). We present the basic characteristics of structural modeling, from which arises the need for proper presentation of the results. SEM is an umbrella term that covers a broad family of procedures with great potential for modeling complex causal relationships. An overview of studies about problems in the reporting SEM results is given, as well as an overview of recommendations on the essential elements of research reports. Given the increasing use of SEM in the social sciences, it is necessary to establish standards for the application and reporting of results in order to ensure the quality and comparability of results. We highlight the issue of choosing model fit indices and point to influential studies addressing it. The aim of the paper is to point out the most common mistakes in presenting the results and to provide basic guidance on how to avoid them, with reference to studies that can shed some light on certain aspects of the problem. Deficiencies in the reports may indicate deficiencies in the research itself, so it is important to avoid them, in order to allow for a valid interpretation, evaluation and replication of the achieved results by the wider scientific community. In order to avoid common application and reporting errors, an attempt was made to form a checklist of basic criteria for reports for studies utilizing SEM, based on the relevant literature. However, it should be noted that SEM procedures are in the process of further development, and further monitoring of their development and refinement of these criteria is necessary.

Keywords: *Structural Equation Modeling, SEM, reporting results, guidelines.*

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STRUCTURAL EQUATION MODELING – AN OVERVIEW OF FUNDAMENTAL CHARACTERISTICS

Structural Equation Modeling (SEM) involves a set of related procedures that allow conclusions to be drawn about the association between latent and manifest variables. It was first applied in 1918, and its application in science has intensified since the 1970s (Teo, Ting Tsai & Yang, 2013: 3). The name of this family of procedures derives from its essential features: a) the relations under study are represented by a set of regression and / or structural equations; b) the examined relationships can be represented by a graphical model, which allows a clearer conceptualization of the problem (Byrne, 2010: 3). SEM enables an objective evaluation of the adequacy of the theoretical model, based on the discrepancies between the assumed and observed interrelations matrix (Raykov, Tomer & Nesselroade, 1991: 499). The great flexibility of SEM stems from the fact that it encompasses a system of regression equations, which means processing multiple equations within a model and allowing the same variable to have predictor status in one equation and criterion status in another (Nachtigall, Kroehne, Funke & Steyer, 2003: 3–4). SEM stands for umbrella term, which includes a variety of procedures such as: path analytic (PA), confirmatory factor analysis (CFA), structural regression (SR) and latent change model (LC) (Teo, Ting Tsai & Yang, 2013: 4). Procedures within SEM can generally be divided into categories: a) measured variable path analysis (MVPA), which models relationships between observed variables, b) confirmatory factor analysis (CFA), modeling relations between manifest and latent factors and c) latent variable path analysis (LVPA), which models relationships between latent factors and includes more complex multilevel models (Mueller & Hancock, 2008: 489). Depending on the type of procedure and aim of application, SEM can be used for theory building, when using exploratory techniques to test connections between constructs, or theory testing, which involves rigorously testing hypotheses about one or more alternative models, that follow from theoretical assumptions (Roberts, Thatcher & Grover, 2010: 4331).

The great advantage of SEM is the ability to include latent variables in the model besides the observed ones. Variables in the model can have the status of exogenous and endogenous variables; endogenous are variables whose changes are estimated in the model (dependent variables), while the sources of change are exogenous variables outside the model (Kline, 2010:, 95). In this sense, SEM procedures are similar to exploratory factor analysis. While most multivariate procedures are predominantly descriptive, SEM requires defining the assumed relationship of variables in the model at the beginning of the procedure and allows testing hypotheses about the specified model, i.e. it is of a confirmatory nature. The confirmatory method provides a means for evaluating and refining theoretical models, and has great potential for the further theory development (Anderson & Gerbing, 1998: 411).

Composite or full structural model can be broken down into two main elements: the measurement model and the structural (path) model. The measurement model represents a set of observed variables that represent indicators of latent variables or factors, and the path model captures the dependency relationships between the factors (McDonald & Ho, 2002: 65–66). In this sense, SEM presents a combination of multiple regression and exploratory factor analysis (Ullman, 2001: 676); or, given the necessity of pre-defining factors and relationships with observed variables, SEM may rather be viewed as a technique that integrates confirmatory analysis and multiple regression (Schreiber, Nora, Stage, Barlow & King, 2006: 325). There are three approaches to confirmatory analysis: a) strictly confirmatory, aimed at testing the adequacy of one assumed model based on the difference in covariance matrices or correlations; b) the development of a model, which is a combination of a confirmatory and exploratory approach, in order to test the adequacy of the model and to modify it in case of inadequacy; c) an alternative model approach, which involves testing the adequacy of multiple predetermined models (Reisinger & Movondo, 2007: 43).

A significant contribution of SEM is reflected in the modeling of causal relationships, however, caution is advised when interpreting causal relationships without experimental design. SEM does not necessarily imply a causal model; it is possible to obtain a model with a good fit that is not affected by the change in the direction of the relationship between the variables (Nachtigall, Kroehne, Funke & Steyer, 2003: 6). As Farbinger, Porter and Norris (2010: 221–222) point out, modeling causal connection is not the same as proving causal connection. Further, like related techniques, such as ANOVA, SEM is not immune to the problems of inference about causal relationships on non-experimental data, but has the advantage of testing alternative explanations for causal relationships; third, establishing a relationship between the dependent and the independent variable by applying SEM should be followed by checking the characteristics of the scales for measuring the independent variable, to determine whether the measuring the construct did not influence the result. Given its flexibility, the ability to model measurement errors, and the inclusion of mediating variables, the predominant use of SEM is unfortunately focused on non-experimental data, although it is also suitable for use on experimental data (Farbinger, Porter & Norris, 2010: 222).

STUDIES OF THE PROBLEMS IN REPORTING SEM RESULTS

The aforementioned advantages have led to the widespread use of this technique in the social sciences, which further leads to the need to establish guidelines for presenting the results of SEM-based analyses (Raykov, Tomer & Nesselroade, 1991: 499). There are several reasons for the inconsistency in the reports of the studies using SEM: “One reason for this gap between the methodological and substantive literatures is that many important methodological findings, by virtue of where they are published and their highly technical nature, are not readily accessible to the typical researcher" (Fabrigar, Porter & Norris, 2010: 221). Given the shortcomings in the presentation of results, it is often difficult to assess the significance and contribution of research in which structural modeling is applied (Boomsma, 2000: 461–462). We further give an overview of the present practices and summarize relevant recommendations and criteria for valid reporting of SEM results.

The main shortcomings in the reporting of structural modeling results are: lack of theoretical basis for the assumed model, insufficient reporting of psychometric scale characteristics, lack of sample selection and sample size data, lack of description of the studied population, and insufficient rationale for modifying the model (Boomsma, 2000: 461). These deficiencies may be due to more serious deficiencies in the analysis process itself and the inadequate implementation of the structural modeling process, therefore it is important to follow the guidelines in writing the report so the credibility of the research methodology is not called into question. McDonald and Ho (2002) found similar shortcomings based on the analysis of 41 scientific papers published in psychological journals from 1995 to 1997. Sample included papers containing a path diagram, which is presented in whole only in 10 articles. The authors state that a theoretical basis should be provided for each assumed relation between the variables (or the absence thereof, which is equally important), but such explanation has not been given in any of the 41 analysed articles (McDonald & Ho, 2002: 66). Information on multivariate normality of the variables was provided in 5 articles, and examined correlation or covariance matrices were available in 19 cases. All studies reported a value of χ^2, which is insignificant in only 5 cases; of the other fit indices the most commonly reported are: URFI and CFI (21 studies), RMSEA (20), GFI (15 studies), TLI (13), NNFI (13) and NFI (9). The parameters are reported in 12 studies and standard parameter estimation errors in 5 articles.

Jackson, Gillaspy and Purc-Stephenson (2009) analyse confirmatory factor analysis reports published by the American Psychological Association (APA) from 1998 to 2006. The sample included 194 articles, selected by searching term "CFA" and "confirmatory factor analysis" in PsychINFO. The results of the study show that examination of univariate normality of variables was reported in 21.6% of cases, and multivariate normality in 13,4%. The estimation method was not reported in 33% of studies, information on the type of analysed matrix was missing in 59.8% studies and the matrix itself was presented in 18,6% of cases. Of the fit indices most frequently reported are χ^2 (89.2%), CFI (78.4%), RMSEA (64.9%) and TLI (46.4%). The choice of fit index was explained in 36.1% studies and criteria for determining the adequacy of the model were specified in 57.2% of cases. The estimated parameters were not specified in 42.7% of cases, and standard errors of parameters were reported by only 12.6% studies. Model validation on separate samples or subsamples was reported in 18.7% studies. A weak correlation was found between validation reporting and model modification, with more commonly reported validation in studies with model modification.

One study in the field of communication science shows that, in addition to the aforementioned shortcomings, there are also errors indicating a lack of knowledge of structural modeling procedures, such as sample size criteria and an incorrect number of degrees of freedom. The research was conducted in 2002 on a sample of 59 articles published from 1995 to 2000 in 37 scientific journals in the field of communications (Holbert & Stephenson, 2002: 538). The analysis excluded articles based on CFA and ordinary least squares (OLS) method of estimation. The authors report that the frequency of SEM-based studies is much lower than in psychological journals, averaging close to 10 articles per year. In 27.1% of articles, the sample size was less than 150. Path diagram was presented in 54% of cases. The number of degrees of freedom was reported in 33.38% of cases, and in 10,2% the stated value was incorrect. The test matrix was presented in 21.2% of papers, the estimation method given in 39%; the value of the estimated parameters is given in 89% and the standard errors of the parameters in 27.1% of cases. The most commonly reported fit index is χ^2 (83.1%), followed by AFS (46.6%), CFI (38.1%). Validation on another sample or subsample was reported in only 4.2% studies.

Results reporting problems have been addressed in multiple studies and attempts have been made to formulate recommendations for creating successful scientific report of results obtained by structural modeling (Raykov, Tomer & Nesselroade, 1991; Hoyle & Panter, 1995; Schreiber, Nora, Stage, Barlow & King, 2006; Boomsma, 2000; Jackson, Gillaspy & Purc-Stephenson, 2009; Kline, 2010). The main objective of proper research reporting is to enable the process to be replicated by the wider scientific community, or readers of the report (Boomsma, 2000: 462). Following these studies we point to fundamental questions to be answered in each phase of SEM application process and to be reported in research paper. The process of applying SEM can be broken down into procedures: model specification, identification, estimation, evaluation and modification; in addition, Kline (2010: 94–95) specifies two additional steps, which are desirable to perform, but this is often not the case in practice: 7) replication of results in an independent sample; 8) application of results, which is reflected in prediction.

RECOMMENDATIONS FOR RESULTS REPORTING

In the introductory section of the paper it is necessary to present the research problem, clearly define the research question and aim of the research. Given the posed question and the aim of the research, an explanation for the choice of structural modeling should be provided and answer why simpler methods, such as correlation or regression analysis, were not selected (Boomsma, 2000: 465). The most important element of SEM is the reliance on theoretical assumptions on the basis of which an empirical model can be specified in the form of a system of regression equations (Nachtigall, Kroehne, Funke & Steyer, 2003: 12). It is important to emphasize the confirmatory/exploratory character of the analysis, which results in the need for validation on independent samples or subsamples in the case of exploratory research. In the case of analysing alternative models, it is necessary to specify them in the introduction and provide a theoretical background for the specification of those models; in the case of nested models, it is advisable to move from simpler to more complex models. The theoretical justification of the assumed connections in the structural model is highlighted by a number of authors; McDonald & Ho (2002: 66) even state that the theoretical justification needs to be stated for each assumed relation in the model as well as for the omitted ones. The direction and expected strength of the assumed relationships need to be explained. The path diagram should be presented rather than mathematical equations and it should be complete, that is, including structural and measurement errors and covariance. The path diagram follows from the conceptual model and shows it in more detail; based on information on measured and latent variables and the presence and absence of links in the path diagram, the reader should have a clear idea of the statistical model as a whole (Hoyle & Panther, 1995: 160). In case of conflict with the rules of the journal in which the paper is published, it is important to provide sufficient information about the model so that the reader can be fully informed of the model structure from the description.

The model identification problem should be investigated at the beginning of the research and reported on the result as well as the fulfilment of structural modeling assumptions. Before applying SEM, it is important to check that the data meets the requirements. To implement SEM, the following assumptions must be satisfied: a) linearity of relations, b) homoskedasticity, c) multivariate normality, d) univariate normality, e) absence of deviation values, e) variables measured at interval or ratio scale, f) sample size 100–400, or minimum ratio of cases and variables 5 : 1, g) validity of measures, h) random sampling, and) error independence (Reisinger & Movondo, 2007: 42). Stricter recommendations regarding sample size imply a 10 : 1 and 20 : 1 ratio of cases and variables (Kline, 2010: 12). It is necessary to report on the reliability of the constructs measures, the instrument used, and the method of scaling the latent variables. To enable model identification, a metric scale of factors must be determined, which is accomplished by fixing the variance of a factor or one arbitrarily determined indicator to a positive value, most commonly 1 (Byrne, 2010: 34–35).

It is necessary to clarify to which population the research and the specified model refer, as precisely as possible; this clarification provides the basis for sample selection and for generalizing the results obtained. Boomsma (2000: 465) believes that this information should be given in the introduction, with a theoretical explanation of the model formulation, however, we emphasize that in addition to the theoretical importance of population determination, it is necessary to indicate the characteristics of the applied sampling, given that the best reasoned and well-fitting model fails if obtained from an inadequate sample. In addition to the description of the population, its size and characteristics, a description of the type and size of the sample should be provided. The key questions are: a) whether a sufficient number of indicators per latent construct has been determined for the model to be identified, or that the parameters have been estimated on the basis of empirical data; b) whether the sample is large enough for a given number of indicators; in addition to general recommendations, the answers to these questions may vary depending on the type of subject and the model formulated, so it is important to consult the relevant methodological literature (Nachtigall, Kroehne, Funke & Steyer, 2003: 13).

The structural model involves testing the discrepancy between the moment matrices obtained on the sample and those assumed by the model, which can be of different nature (covariance or correlations), but one can find in the literature that a covariance matrix should always be used (Hoyle & Panther, 1995: 161). It is necessary to specify the type of test matrix, justify this choice, and, if possible, display the matrix. If the matrices are too large to insert into the paper itself, it should be possible for readers to gain access otherwise; for example, provide a web-site where content is available. The most commonly used estimation methods in SEM are: maximum likelihood (ML), ordinary least squares (OLS), generalized least squares (GLS), and weighted least squares methods (WLS) (McDonald & Ho, 2002: 69). The choice of method depends on the characteristics of the variables, their distributions, the sample size, and the analysed moment matrix. Software used for analysis can affect the obtained results, depending on the mode of application procedures, so one should always specify which program is used to analyse and which version of the program.

The choice of model adequacy measures depends largely on the model structure and data on which the analysis was conducted, but general guidance can be given. Any data irregularities (identification problems, Heywood cases, etc.) should be reported. Then, of major interest are model fit indices, parameter estimates, and standard errors of the estimated parameters. The initial measure of the SEM model estimation is the χ^2 test statistic, an absolute fit index which shows discrepancy between the assumed and observed matrix; the null hypothesis is that there is no difference between matrices, so an insignificant χ^2 is desirable. The aforementioned measure shows the disadvantages of: a) variation with respect to sample size – it is possible to get a false significant statistics with large samples; b) concluding absence of fit does not provide relevant information on the degree of deviation or which elements deviate; c) given the complexity of the phenomena studied, especially in the social sciences, one should not expect a complete match of matrices, but rather seek an approximation to reality (McCoach, Black &

O'Connell, 2007: 463). Due to the mentioned shortcomings, it is necessary to apply other fit indices besides χ^2 to evaluate the adequacy of the model. However, a significant χ^2 test should not be neglected and resort to the use of other indices to mask model inadequacy (Barrett, 2007: 819–820).

Approximate fit indices can be divided into several categories: a) absolute fit indices show the proportion of variance explained by the model, b) incremental or comparative indices show the relative contribution of the model to the explanation, relative to the null model assuming independence between variables, c) parsimony indices evaluate the contribution of the model with respect to complexity, i.e. number of parameters, d) predictive indices, which evaluate the adequacy of the model in a hypothetical replicated sample (Kline, 2010: 195–196). McDonald and Ho (2002: 72) outline four well-known problems in selection and interpretation of fit indices: a) lack of empirical and mathematical basis for their use; b) lack of compelling evidence for relative preference over absolute indices; c) the lack of strong correlation between the indices, which would mean that a decision based on one index dose not point to the same decision based on another; d) rejection of the model as inadequate may be caused by several large deviations due to poor specification and it is not possible to determine which aspects of the model are wrong only on the basis of the fit index.

Structural modeling provides a wide range of model adequacy measures, leading to two questions: a) what measures should be selected and reported; b) what criteria indicate acceptable model adequacy? (Hu & Bentler, 1999: 4). In answer to these questions usually are applied the criteria that stems from the influential study conducted by Hu and Bentler in 1999. In the study of the mentioned authors, two types of models (simple and complex models) were used to obtain the index values under different conditions. Both types of models include 15 observed variables and three latent ones; one accurately specified and two incorrectly specified models were formed for each type. The results show that indices obtained through maximum likelihood (ML) methods are more efficient and preferable than indices estimated by the generalized least squares (GLS), and asymptotically distribution-free (ADF). Of the indexes, SRMR is most sensitive to factor misstatements, followed by TLI, BL89, RNI, CFI, Gamma Hat, Mc, and RMSEA (Hu & Bentler, 1999: 16). ML indices were found to behave similarly, while SRMR scores differed, so the use of two indices was recommended; SRMR and one of the ML indexes. The authors propose criteria for determining model adequacy, which minimize type I error and type II error. The recommended criteria for determining the adequacy of the model are: SRMR <0.08; TLI, RNI, CFI, BL89>0.95; RMSEA<0.06 (Hu & Bentler, 1999: 27). Kline (2010: 204) recommends the use of four indices that describe the adequacy of the model from different aspects: a) RMSEA, b) GFI, c) CFI, d) SRMR.

The reporting two fit indices strategy for the has been implemented in 11.8% of psychology studies from 2000 to 2006; the frequency of reporting shows no signs of change during this period, although it has been elevated in the last examined year (28,6% of articles) (Jackson, Gillaspy & Purc-Stephenson, 2009: 15). Although the proposed guidelines by Hu and Bentler are generally accepted there are caveats in subsequent studies that they should not be mechanically applied. The group of authors repeated the research, applying a modified study design and rethinking the suggested guidelines (Sivo, Xitao, Witta & Willse, 2006). The authors based the analysis on the same three models as Hu and Bentler, applying a fully crossed design, so that each model was viewed as an accurately specified model. The results indicate that the criteria are influenced by the sample size, so they need to be less rigorous for smaller samples. This conclusion applies to incremental indices, while parsimony indices values primarily depend on the number of degrees of freedom of the model, and the authors consider that no general standards should be set for these indices (Sivo, Xitao, Witta & Willse, 2006: 284–285). Marsh and associates also indicate that in the procedure applied by Hu and Bentler, the criteria for evaluating model adequacy vary depending on the characteristics of the model being labelled as incorrectly specified (Marsh, Hau & Wen, 2004: 337). The authors believe that such guidelines for using the indices should not be equated with the "golden rule" that is universally applicable, and emphasize that both Hu and Bentler warned of the limited generalizability of their study results and the need for further (Marsh, Hau & Wen, 2004: 322). As there is no universal solution or a generally accepted criterion for selecting a fit index, other options for assessing the adequacy of the SEM model should be considered, such as equivalence testing (Marcoulides & Yuan, 2016).

After the fit indices, the size of the parameters should be discussed, i.e. the strength of the assumed relations between the variables, as well as the direction. There is a danger of overestimating the importance of model fit without discussing the obtained parameters within the logical settings of the model (Fabrigar, Porter & Norris, 2010: 223). To enable parameter reliability estimation, standard parameter errors and p values should also be presented. Significance of statistics may depend on the sample size, so it is not advisable to exclude predictors only on the basis of non-significant p value (Kline, 2010: 217).

Model evaluation, after evaluating statistical measures, involves theoretical explanation of the results obtained and interpretation of: a) size and sign of parameters in case of adequate model, b) modification of model in case of inadequate model, after excluding other potential reasons for inadequacy (sample size, impaired assumptions, etc.). Any modification must be theoretically justified and meaningful. The author should report: a) a test assessing the effect of the modification, b) the reason for choosing the test, c) the theoretical justification for the modification (Schreiber, Nora, Stage, Barlow & King, 2006: 327). In the process of modification, the question of equivalent models should be considered. The most challenging part of structural modeling inference is in the direction of relationships; in many models, by changing the direction of the relation, the adequacy of the model and the parameter estimates do not change significantly, so the direction of the effect must be estimated on the basis of logical and theoretically argued criteria (Hoyle & Panter, 1995: 175). It should be noted that the parameters in SEM are evaluated simultaneously, and the latent constructs can vary in different models (Nachtigall, Kroehne, Funke & Steyer, 2003: 15). After modification, validation of the model, on an independent sample or subsample, and the evaluation of the statistical power of the analysis should be undertaken. It should be borne in mind that the modification of the model implies a move towards exploratory analysis, especially in the case of insufficient theoretical justification (Raykov, Tomer & Nesselroade, 1991: 502).

Therefore, the exploratory/confirmatory dimension should not be viewed as a dichotomous one, but as an ordered progressive continuum (Anderson & Gerbing, 1998: 412). Modification of the model must always be guided by theoretical assumptions, and not blindly aim at the fit of the model: “Model fit is maximized by introducing theoretically meaningless paths and error covariances instead of finding the optimum in balance with the parsimony principle that the simplest of similar models is the better choice. The result of such “post hockery” and “fitishism” is a model that fits the particular data of the sample without a chance of being reproduced in other populations.” (Nachtigall, Kroehne, Funke & Steyer, 2003: 15).

In assessing model adequacy, Anderson and Gerbing (1988: 418) propose a two-stage strategy: assessing the adequacy of the measured model in the first step and assessing the adequacy of the structural model in the second step. The authors state that the implementation of this strategy avoids model specification errors and interpretational confounding, or attribution of false meaning to factors. To implement this approach, the authors recommend testing nested models from zero to saturated:

$$Mn < Mc < M < Mt < Ms$$

In the above sequence, Mn is the null model, Ms is saturated and M is the assumed model. Mc and Mt are modified models, Mc with one limited parameter, and Mt with one additional parameter. This provides a framework for comparing models and examining alternative models possible within a given theory (Anderson & Gerbing, 1988: 422). However, there are limitations in this approach that should be borne in mind. Fornell and Yi (1992: 295) point to the assumptions that follow from the two-stage strategy and can be problematic to fulfil: a) presumed independence of theory and measurement, b) validity of the measurement established in the first step can be generalized to other model specifications, c) estimators in two-stage strategy are asymptotically unbiased, consistent and effective, d) statistical tests from one stage are independent from the tests of the other stage.

Discussion should be started by repeating the most significant results identified in the analysis, linking them to the theory and findings of previous research initially presented. In addition to interpreting the results within a theoretical context, it is important to look at the possibilities of generalizing the results and limitations of the study, arising from the applied method. Therefore, in accordance with the aforementioned guidelines for the application of SEM, the results should be interpreted within the limits of validity for the selected population and generalized according to the characteristics of the sample. Finally, it is necessary to point out the questions that have been raised in the research and the direction in which future studies should go.

CONCLUSION

Based on the presented standards for SEM implementation and analysis reporting, the basic guidelines for a SEM-based research report can be summarized as follows:

1. Make clear the theoretical basis for the specified model and explain expected relationship between variables and factors (including direction)
2. Explain variable measurements and scale characteristics (pay attention to model identification)
3. Present graph of the path diagram if possible
4. Specify population accurately (determine limits of generalization of results)
5. Make sure to specify the sample type and the sample size (to enable the evaluation of the generalizability of the results)
6. Display characteristics of the data and examine whether they meet the criteria for the application of SEM
7. Display the analyzed moment matrix
8. State and explain the choice of estimation method
9. Specify appropriate criteria for model acceptance / rejection (with consultation of relevant literature), fit indices, values and statistical significance of estimated parameters and standard errors of parameters
10. In case of model modification, explain the reasons and theoretical background for the modification
11. Interpret results in accordance with theory, generalization possibilities with respect to population and sample characteristics, limitations and respecification of model.

The items in the listed checklist are presented in more detail and explained in the previous section. It is important to note that these are basic guidelines that should certainly be supplemented by referring to the relevant literature according to the specific characteristics of the particular application method (depending on the specific subtype of SEM procedures, selection of method of assessment, chosen fit indices, etc.). The paper highlights some of the most significant problems with SEM implementation and information on how to address these issues that need to be reported but the list of the requirements for reporting on results has not been exhausted.

The problematic structural modeling analysis reports call into question the credibility of the work and the procedures implemented. Therefore, when writing a report, the most common mistakes should be kept in mind and efforts should be made to avoid them. Guidelines for communicating results can be very helpful; not only when it comes to recommendations that relate specifically to structural modeling reporting, but also general guidelines for writing scientific papers. It has already been noted that deficiencies in the report may be due to deficiencies in the knowledge of the statistical procedure itself and its methodological implications; therefore, it is necessary to determine the degree of knowledge of the characteristics of SEM before starting the research. In addition to examining the basic literature, it is useful to examine the errors that occur in the application of procedure. The main guideline to follow is that the report should allow for the replication of the research by an expert reading audience. The necessity to adhere to the rules of the scientific journal for which the paper is being prepared should also be kept in mind and aim to find the optimal way to comply with the defined requirements and recommendations of proper reporting of results.

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