Why We Need to Abandon Fixed Cutoffs for Goodness-of-Fit Indices:

A Comprehensive Simulation and Possible Solutions

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Abstract

To evaluate model fit in confirmatory factor analysis, researchers compare goodness-of-fit indices (GOFs) against fixed cutoff values (e.g., CFI > .95) derived from simulation studies. However, methodologists have cautioned that cutoffs for GOFs may not be as broadly applicable as researchers commonly assume. Especially in settings not covered in the simulation scenarios from which cutoffs were derived, these cutoffs may no longer be valid. However, how serious these issues with cutoffs are is not fully clear. Here we present the most comprehensive simulation study to date on (1) the sensitivity of GOFs to model misspecification and (2) the susceptibility of GOFs to further data and analysis characteristics (i.e., estimator, number of indicators, number and distribution of response options, loading magnitude, sample size, and factor correlation). Our simulation enables us to uncover several previously unknown or at least underappreciated issues with GOFs. All widely used GOFs (χ^2 , χ^2/df , CFI, RMSEA, SRMR) are far more susceptible to data and analysis characteristics than commonly assumed (e.g., factor correlation). Moreover, the sensitivity of GOFs to misspecifications in factor dimensionality or cross-loadings varies greatly across different scenarios in complex and hard-to-predict ways. The varying sensitivity and strong susceptibility of GOFs to multiple data and analysis characteristics suggest that the practice of judging models fit against fixed cutoffs for these GOFs is highly problematic. They imply that there can be no universally applicable “golden rules.” We discuss several time-honored and emerging strategies for assessing model fit. We argue that tailored cutoffs are the way forward.

Translational Abstract

To evaluate model fit in confirmatory factor analysis, researchers compare so-called goodness-of-fit indices (GOFs) against fixed cutoff values (e.g., CFI > .95). These cutoffs were derived from simulation studies. Although researchers commonly use such fixed cutoff values, methodologists have cautioned that one should only apply fixed cutoffs in settings similar to the simulation scenarios from which cutoffs were derived. This is because GOFs may behave differently in different empirical settings. Absolute values of GOFs differ depending on the degree of misspecification, as intended. Unintendedly, values of GOFs also vary depending on the data and analysis characteristics of the empirical setting in which one applies them. The extent to which absolute values of GOFs differ in various empirical settings is not fully clear yet. We present the most comprehensive simulation study to date on (1) the extent that GOFs can detect model misspecification in various settings and (2) the extent that GOF values change depending on data and analysis characteristics of various settings (i.e., estimator, number of indicators, number and distribution of response options, loading magnitude, sample size, and factor correlation). Various data and analysis characteristics other than the model misspecifications influence all widely used GOFs (χ^2 , χ^2/df , CFI, RMSEA, SRMR). Furthermore, the ability of GOFs to detect misspecification also varied greatly depending on several data and analysis characteristics. The dependence of GOFs on a variety of extraneous characteristics suggests that one cannot use a fixed cutoff across diverse empirical settings. We discuss alternative strategies for assessing model fit.

Keywords: goodness-of-fit, fit index, ordered categorical data, confirmatory factor analysis, structural equation modeling

67 **Are Goodness-of-Fit Indices Any Good? Why We Cannot be so Sure**

68 In social and behavioral science research, researchers commonly employ goodness-
69 of-fit indices (GOFs) to evaluate the fit of latent variable models such as confirmatory factor
70 analysis (CFA) models. The most widely used GOFs are the chi-square test statistic divided
71 by the model degrees of freedom (χ^2/df), the comparative fit index (CFI), the root mean
72 square error of approximation (RMSEA), and the standardized root mean square residual
73 (SRMR). In addition, researchers often rely on the traditional chi-square test statistic of exact
74 model fit (χ^2). Although strictly speaking not a GOF but a formal test, researchers use χ^2 in
75 much the same way as they use GOFs (see also Jöreskog & Sörbom, 1993), which is why we
76 henceforth subsume it under the same rubric.

77 Cutoffs for GOFs, on which binary decisions about accepting or rejecting a model
78 rest, were derived from simulation studies. Simulation studies represent highly controlled
79 settings in which—different from the analysis of real data—researchers know and have
80 control over the population (or data-generating) model. Researchers specify a population
81 model, simulate data based on that model, and introduce model misspecifications of known
82 size in the analysis model. Then, they examine how GOFs respond to such misspecifications.
83 Based on the distribution of GOFs, researchers derive cutoffs for these GOFs in such a way
84 that a critical level of misspecification leads to model rejection. What constitutes a “critical”
85 level of misspecification, and hence a reasonable cutoff, is a somewhat arbitrary decision. In
86 the past two decades, the cutoffs suggested by Hu and Bentler (1999) have been by far the
87 most prominent and widely used ones, with their article boasting more than 70,000 citations
88 on GoogleScholar at the time of this writing. According to these authors, $CFI \geq .950$,
89 $RMSEA \leq .060$, and $SRMR \leq .080$ point to good model fit. Reußner (2019) or Rutkowski
90 and Svetina (2014) have proposed similar cutoffs. Though based on statistical principles

rather than derived from simulation studies, the observed χ^2 value should not differ significantly from a critical χ^2 value to indicate a well-fitting model; the critical χ^2 value varies with the model degrees of freedom (Bollen, 1989; see Moshagen & Erdfelder, 2016, for additional suggestions on critical values). Ullman (2014) suggested that a ratio of χ^2/df below 2 indicates a well-fitting model.

However, there are severe problems with the common practice of relying on fixed cutoffs for GOFs in model evaluation (e.g., McNeish & Wolf, 2021). These problems appear not yet to be widely recognized by applied researchers. The key underlying issue is that simulation studies can only cover a limited set of scenarios. These scenarios are far from covering all possible combinations of data and analysis characteristics that researchers will encounter in applied settings. If GOFs only reacted to model misspecification predictably and uniformly, the constraints of simulation studies would not pose a major problem. If, by contrast, GOFs reacted differently to specific types of misspecification not considered in the simulation studies, the cutoff values for GOFs may not apply to these types of misspecification. Graver still, if GOFs reacted not only to misspecification but also to other characteristics of the data and analysis, their validity for judging the model fit may be severely compromised. We henceforth refer to the undesirable dependence of GOFs on data and analysis characteristics as *susceptibility* and contrast it with their desirable *sensitivity* to misspecification. Such susceptibility to data and analysis characteristics of GOFs is no purely hypothetical concern. Although GOFs are designed to quantify the degree of model misspecification and should ideally not react to any data or analysis characteristic, they apparently do. As we detail in the following, previous simulations suggest that GOFs are, for instance, susceptible to the type of estimator and the number of response options (Xia & Yang, 2018, 2019).

It follows that established cutoffs for GOFs are sufficiently certain to be valid only in empirical settings (i.e., combinations of data and analysis characteristics) that closely resemble the scenarios covered by the simulations from which these cutoffs were derived. The range of scenarios covered by existing simulations is dwarfed by the diversity and complexity of empirical settings encountered in applied research. Consequently, cutoffs for GOFs may lack external validity, and blindly applying the same set of cutoffs to a multitude of different empirical settings can mislead researchers into erroneous conclusions about model fit and substantive questions.

Unfortunately, current reporting practice shows that researchers apply the same cutoffs in the presence of data or analysis characteristics that can differ markedly from the ones in the simulation studies. It appears that concerns regarding overgeneralizations of cutoffs (e.g., Heene et al., 2011; Markland, 2007; Marsh et al., 2004; McNeish & Wolf, 2021; Niemand & Mai, 2018; Nye & Drasgow, 2011) have gone largely unheeded. The widespread, or in fact near-universal, practice of relying on (fixed) cutoffs for GOFs in model evaluation is disconcerting given the ongoing uncertainty about the applicability of fixed cutoffs for GOFs to scenarios hitherto uncharted by simulation studies.

Just *how* problematic is the practice of using fixed cutoffs for GOFs? In the following, we review extant research on the susceptibilities of GOFs to data and analysis characteristics. Following our review of the susceptibilities, we present a simulation study that considerably extends previous simulations and represents the most comprehensive simulation on the sensitivity and susceptibility of GOFs obtained from CFA models to date. Our results sound the highest level of alarm for the validity of fixed cutoffs for GOFs. As a way forward, we discuss several time-honored and promising emerging alternatives for model fit evaluation that do not rely on fixed cutoffs, particularly tailored cutoffs.

Susceptibilities of GOFs to Data and Analysis Characteristics:

A Review of Previous Findings

GOFs are intended to enable evaluations of model fit, specifically, to help detect non-negligible model misspecification.¹ However, previous investigations showed that GOFs are susceptible to various data and analysis characteristics other than model misfit (e.g., Beauducel & Herzberg, 2006).² Moreover, different characteristics appear to interact with each other in complex ways.

¹ Researchers often assume that GOFs can detect all types of misspecification. As Hayduk (2014) demonstrated, χ^2 , which is incorporated in χ^2/df , CFI, and RMSEA, cannot detect any misspecification in certain constellations of population and analysis models. The analysis model may appear to fit perfectly, although a different population model has generated the data. We hereby acknowledge the existence of close-fitting models that are seriously misspecified.

² We term the influences of data and analysis characteristics on GOFs as “problems” or “susceptibilities,” even though many of the problems are natural (and sometimes even desirable) consequences of the statistical properties of GOFs. Especially the dependence of χ^2 on sample size is readily comprehensible. As a strict and formal test, rather than a GOF proper, χ^2 depends on the model degrees of freedom. Per definition, the power of χ^2 to detect model misspecification increases as the sample size grows (for details see, for instance, Moshagen & Erdfelder, 2016). However, from the perspective of applied researchers, it would be desirable for GOFs to quantify the degree of model misspecification across many

Probably the most familiar example is the susceptibility of GOFs to sample size. All else being equal, χ^2 , χ^2/df , CFI, RMSEA, and SRMR signaled better model fit with increasing sample size for correctly specified models (e.g., Beauducel & Herzberg, 2006; F. Chen et al., 2008; DiStefano et al., 2019; Kenny et al., 2015; Sharma et al., 2005; Shi et al., 2019). For misspecified models, χ^2 , χ^2/df , and RMSEA indicated worse model fit with increasing sample size, whereas CFI and SRMR suggested better model fit (e.g., Beauducel & Wittmann, 2005; DiStefano et al., 2019; Nye & Drasgow, 2011).

Furthermore, GOFs depend directly on the estimator used. Researchers mainly apply maximum likelihood (ML) or its robust cousin MLR, implying parameter estimation based on unstandardized covariances or Pearson correlations. Diagonally weighted least squares (DWLS) based on polychoric correlations or its mean and variance adjusted (WLSMV) test statistic and standard errors are less commonly applied. However, they are gaining relevance as more and more researchers note their utility for ordered-categorical data, such as data from rating scales (Li, 2016). Generally, the DWLS-/WLSMV-based χ^2 , CFI, and RMSEA pointed to better model fit than the ML-based ones (Beauducel & Herzberg, 2006; Nye &

data and analysis characteristics, irrespective of other considerations such as sample size or other empirical features. That is, GOFs should ideally reflect model misspecifications only—any other influences on GOFs are undesirable (e.g., Schermelleh-Engel et al., 2003).

Therefore, we label any influences on GOFs other than misspecifications as problematic from an applied researcher's perspective.

Drasgow, 2011; Xia & Yang, 2019).³ The DWLS-based SRMR indicated worse model fit than the ML-based SRMR for correctly specified models (Beauducel & Herzberg, 2006).

The number of indicators also influences GOFs though in interaction with sample size. At small sample sizes (e.g., $N = 100$), χ^2/df , CFI, and RMSEA indicated worse model fit when indicators of similar psychometric quality were added to a correctly specified model (Kenny & McCoach, 2003; see also Sharma et al., 2005; Shi et al., 2019). At large sample sizes ($N = 1,000$), CFI was no longer affected by the number of indicators, but χ^2/df and RMSEA pointed to better model fit as the number of indicators increased (Kenny & McCoach, 2003). Per statistical definition, χ^2 increases when adding indicators without further restrictions to the model (Bollen, 1989). Looking at misspecified models of the same type (e.g., those with misspecified factor dimensionality), RMSEA pointed to better fit with an increasing number of indicators (DiStefano et al., 2019; Kenny & McCoach, 2003; Savalei, 2012; Shi & Maydeu-Olivares, 2020; Shi et al., 2019). In contrast, χ^2 , χ^2/df , CFI, and SRMR pointed to worse fit with an increasing number of indicators (DiStefano et al., 2019; Kenny & McCoach, 2003; Shi et al., 2019). However, Shi, Maydeu-Olivares, and DiStefano (2018) only found the effect of model size on SRMR for models with unmodeled cross-loadings but not misspecified factor dimensionality. Adding indicators to the model is one way to vary the model complexity. Beauducel and Herzberg (2006) and Fan and Sivo (2007), for instance, varied the model complexity by changing the number of indicators *and*

³ Savalei (2020) proposed an analytical correction to DWLS-/WLSMV-based GOFs to make them appear like ML-based ones, which has not been implemented in major statistical programs like R or Mplus yet.

the number of factors. Moshagen (2012) and Shi, DiStefano, et al. (2018) showed that the number of indicators rather than the number of factors drive the effects of model complexity on model fit.

Xia and Yang (2018) showed that the number and distribution of response options directly influence DWLS-/WLSMV-based GOFs (i.e., χ^2 , χ^2/df , CFI, and RMSEA) under misspecification, as both characteristics determine the precision of polychoric correlations. The precision of polychoric correlations features in the fit function of DWLS and the WLSMV-specific adjustment of the χ^2 test statistic, which transfers to χ^2/df , CFI, and RMSEA. Fewer response options and extremely asymmetric response distributions entail lower precision and, ironically or precisely due to loss of precision, appear as better model fit on the surface compared to more fine-grained response options and more symmetric distributions (see also DiStefano et al., 2019; Shi & Maydeu-Olivares, 2020). With a few response options, WLSMV-based GOFs (i.e., χ^2 , CFI, and RMSEA) of correctly specified models showed better fit than with more response options (Beauducel & Herzberg, 2006). Only the DWLS-based SRMR indicated better model fit with more response options in the study of Beauducel and Herzberg (2006). Yet, ML-based GOFs (i.e., CFI, RMSEA, and SRMR) are susceptible to the skewness of the distribution in a misleading way: An asymmetric compared to a symmetric response distribution yielded worse fit for correctly specified models but better fit for misspecified models (Reußner, 2019).

The magnitude of factor loadings impacts GOFs as well. When the residuals varied with loading magnitude (e.g., higher loadings went along with lower residual variances), GOFs (i.e., χ^2 , RMSEA, and SRMR) suggested worse fit of misspecified models with higher loadings. This implies that researchers' chances to uncover false models diminish whenever the discrimination of indicators is less than optimal (Beierl et al., 2018; Hancock & Mueller,

204 2011; Heene et al., 2011, McNeish et al., 2018; Shi et al., 2019; Shi & Maydeu-Olivares,
205 2020; Shi, Maydeu-Olivares, & DiStefano, 2018, even found an interaction of
206 misspecification and factor loadings on SRMR, which exaggerated the initial effect; cf.
207 Moshagen & Auerwald, 2018, who kept the degree of misspecification and residual error
208 variances constant). CFI behaved different from all other GOFs as studies found mixed
209 effects of higher loadings for misspecified models. For instance, CFI indicated worse model
210 fit with higher loadings in the study of Beierl et al. (2018), better fit in the study of Heene et
211 al. (2011), and Hancock and Mueller (2011) described a U-shaped effect of loading
212 magnitude on CFI for misspecified models. For correctly specified models, CFI and SRMR
213 indicated better model fit with higher loading magnitude in the studies of Beierl et al. (2018),
214 Heene et al. (2011), and Shi et al. (2019).

215 Besides loading magnitude, researchers have also investigated the effects of other
216 model parameters on GOFs. They found that GOFs (i.e., χ^2 , CFI, RMSEA, and SRMR) tend
217 to be impervious to the magnitude of factor covariance/correlation in correctly specified
218 multidimensional models (Beauducel & Herzberg, 2006; Beierl et al., 2018). However, prior
219 research has not yet investigated the influence of factor covariance/correlation on GOFs in
220 misspecified models.

221 As the above literature review reveals, there are already several indications that
222 GOFs are more susceptible to extraneous influences (other than misspecification) than
223 applied researchers appear to appreciate. Prior research has investigated the impact on GOFs
224 of sample size, response distributions, and the number of indicators in tandem (e.g.,
225 Reußner, 2019). This is important because it can reveal how such factors interact. Other
226 research has investigated the effects of the number of response options and type of estimator
227 on GOFs in tandem (e.g., Xia & Yang, 2019). Another strain of research has repeatedly

explored the effects of different magnitudes of factor loadings on GOFs (e.g., Beierl et al., 2018; Heene et al., 2011; Shi et al., 2019). The effect of factor covariance (or correlation) has received the least attention. Crucially, however, no prior simulation study has investigated all aforementioned influences on GOFs in tandem. Therefore, it remains unclear how susceptible GOFs are to the joint influences of these characteristics, including not only the presence of multiple main effects but also how interaction terms between these factors (e.g., sample size $\times$ number of response options) attenuate or aggravate any known biases of GOFs.

The Present Simulation

Aims of the Simulation

In our Monte Carlo simulation study (for more details on Monte Carlo simulations, see Boomsma, 2013), we extend previous simulations by taking a closer look at the impact of a wide range of data and analysis characteristics on GOFs. We seek to provide answers to two questions. First, which data and analysis characteristics—other than the model misspecifications GOFs were designed to detect—influence GOF values the most? This question concerns the *susceptibility* of GOFs to data and analysis characteristics. Second, does the sensitivity of GOFs to detect model misspecifications likewise depend on such characteristics, and in what ways? This question concerns multiple influences on the *sensitivity* of GOFs to detect misspecification.

To ensure external validity, we designed our simulation to cover a wide range of realistic scenarios typically encountered in behavioral and social science research. Each of these scenarios comprised (1) a population model with various characteristics, (2) 1,000 randomly drawn samples of varying size based on that population model, (3) and a correctly specified or misspecified analysis model that we fit to each randomly sampled data through

different estimators. We considered two types of misspecification: misspecification due to factor dimensionality and misspecification due to unmodeled cross-loadings. We varied a total of seven different data and analysis characteristics: type of estimator, number of indicators, number of response options, distribution of response options, loading magnitude, sample size, and, where applicable, factor correlation. In so doing, we considerably expanded the range of scenarios compared to previous simulation studies on GOFs, which varied about three (e.g., estimator, distribution of response options, sample size, Hu & Bentler, 1998) or four (e.g., estimator, model size, number of response options, sample size, Beauducel & Herzberg, 2006) characteristics in total. We then computed GOF statistics for each analysis model. We analyzed the results to answer which data and analysis characteristics impact absolute values of GOFs (susceptibility) and their ability to detect model misspecifications (sensitivity).

Characteristics of the Simulation

Below, we detail each of the characteristics that we varied across the different scenarios in our simulation. We focus on CFA models in our simulation. CFA models (i.e., measurement models) are uniquely important within the latent variable modeling framework, as they are the basis for many structural models. Table 1 provides a summary of the different scenarios.

[please insert Table 1 about here]

Population and analysis model. To cover a breadth of models that may occur in real-world settings, we focused on different combinations of population and analysis models: In the first combination, our population model was either a one-factor or correlated two-factor

model. We fit a one-factor analysis model to data generated from both types of population models. Thus, each analysis model was either correctly specified or misspecified regarding factor dimensionality.

In the second combination, our population model was a two-factor model either without or with cross-loadings. We fit a two-factor analysis model without any cross-loadings to data generated from both types of population models. Thus, each analysis model was either correctly specified or misspecified regarding cross-loadings. Additionally, depending on the factor correlation, the two factors of the population and analysis models were either allowed to correlate or forced to be uncorrelated.

Figure 1 shows the population and analysis models of the scenarios with misspecified factor dimensionality. Figure 2 shows the ones with unmodeled cross-loadings (one instantiation with two cross-loadings and correlated factors displayed). All factors in the population models were latent variables with unit variance and zero mean. Residual variances of the observed indicators depended on the population model parameters to obtain standardized observed indicators. Analysis models achieved identification by fixing the loading of the first indicator of each factor to unity.

[please insert Figure 1 about here]

[please insert Figure 2 about here]

Magnitude of misspecification. In analysis models with misspecified factor dimensionality, we tested one-factor models though the population model was, in fact, a two-factor model with factor correlations of either $r = .70$, $.50$, or $.30$. Thus, from the perspective

that two perfectly correlated factors ($r = 1.00$) are statistically indistinguishable from a one-factor model, the magnitude of the induced misspecification in these scenarios amounted to $r = .30, .50$, and $.70$, respectively. In analysis models with unmodeled cross-loadings, the cross-loadings of the population model had a standardized size of either $.20$ or $.30$ and were consistently lower than the loadings on the primary factor (which ranged from $.40$ to $.80$; see below).

Proportion of misspecification. Whereas we only manipulated one parameter in scenarios with misspecified factor dimensionality (i.e., the factor correlation in a two-factor population model), we manipulated different numbers of parameters in scenarios with unmodeled cross-loadings (i.e., numbers of cross-loadings). In those scenarios, either 17% or 33% of all indicators had cross-loadings.

Estimator. We estimated each analysis model with four estimators: ML (Bollen, 1989), MLR (L. K. Muthén & B. O. Muthén, 1998-2017; Yuan & Bentler, 2000), DWLS, and WLSMV (B. Muthén, 1984; B. Muthén et al., 1997). ML estimation requires the assumptions of multivariate normal and continuous data. Robust ML (MLR) estimation assumes continuous data but corrects the χ^2 test statistic and standard errors of ML-estimated parameters for non-normality with the help of scaling factors. Here, we analyze the commonly used Yuan and Bentler (2000) correction of the χ^2 test statistic. ML/MLR estimation yields relatively unbiased model parameters for ordered categorical data with a sufficient number of response options (i.e., five or more; Beauducel & Herzberg, 2006; Rhemtulla et al., 2012). DWLS makes no assumption about the underlying distribution of the observed indicators and takes the ordered categorical data structure into account. The same applies to WLSMV, which corrects the DWLS-based χ^2 test statistic to follow a chi-square distribution, and it corrects the standard errors for loss of efficiency during the

DWLS-based estimation procedure (for an overview of the estimation procedures, see Li, 2016). Unlike ML/MLR, DWLS and WLSMV include thresholds in the model parameterization that define the utilization of response options depending on the standing of the latent variable. To identify the DWLS/WLSMV-based analysis model, we followed the procedure outlined by Millsap (2011) in line with the theta parameterization. Unlike the delta parameterization, which fixes the residual variances of the observed indicators to one, the theta parameterization scales the distribution of intermediate continuous latent response variables by fixing their variances to one.

Number of indicators. All population and analysis models comprised either six or 12 observed indicators in total. Thus, the one-factor models had either six or 12 indicators. In the two-factor model scenario, each factor had three or six indicators, ensuring the minimum number of indicators required for model identification in the absence of further constraints. The number of indicators reflected a typical range for psychological short scales, for which 12 or fewer indicators per factor are common (Rammstedt & Beierlein, 2014).

Response options. The ordered-categorical indicators had three, five, or seven response options. The number of response options is in line with standard Likert-type formats in personality research, typically containing three to seven options (Clark & Watson, 2019; Simms et al., 2019).

Distribution of responses. The distributions of the observed indicators in our simulation were either symmetric or asymmetric. In a meta-analysis, Blanca et al. (2013) found that 34% of the empirical data reanalyzed in their study had slight skew in the range of -0.25 to $+0.25$. Most data in their meta-analysis fell into the near-normal range, which we label *symmetric* here. The second-largest share of their data (24%) had slight positive skew in the range of $+0.26$ to $+0.75$, which we call *asymmetric* here. Building on this meta-

analysis, we chose our distributions to be either symmetric ($\text{skew}_{\text{symmetric}} = 0.00$) or moderately skewed ($\text{skew}_{\text{asymmetric}} = 0.65$). The excess was around -0.80 across scenarios. Skew was always zero or positive, and excess was always negative.

To obtain ordered categorical indicators and determine the shapes of the resulting response distribution (i.e., symmetric or asymmetric), we cut the initially continuous data by setting different thresholds. To simulate a symmetric distribution of responses, we set thresholds to produce three (thresholds/z-values: $-0.75, +0.75$; with corresponding frequency percentages: 23%, 54%, 23%), five (thresholds/z-values: $-1.20, -0.40, +0.40, +1.20$; percentages: 12%, 23%, 31%, 23%, 12%), or seven equidistant response options (thresholds/z-values: $-1.25, -0.75, -0.25, +0.25, +0.75, +1.25$; percentages: 11%, 12%, 18%, 20%, 18%, 12%, 11%). To simulate an asymmetric response distribution, we shifted these response options to thresholds/z-values of $+0.00, +1.04$ (percentage: 50%, 35%, 15%) for the scenario with three response options; $-0.39, +0.31, +0.74, +1.28$ (percentage: 35%, 27%, 15%, 13%, 10%) for five response options; and $-0.52, +0.00, +0.35, +0.64, +0.99, +1.40$ (percentage: 20%, 20%, 15%, 15%, 10%, 10%, 10%) for seven response options.

Loading magnitude. All population models had homogeneous loading magnitudes of either .40, .60, or .80 to cover a wide range of loadings typically encountered in individual difference research. For instance, primary factor loadings of the personality inventory BFI-2 range between .39 and .80 (Soto & John, 2017). For simplicity, all indicators shared the predetermined loading magnitude on all factors within each population model, although, in reality, loadings may vary. By keeping loadings equal across indicators within each population model, we preserved the numerical distances between lower and higher loading magnitudes. It allows for easier tracking in subsequent analyses (described below).

Sample size. We varied sample sizes at 200, 500, and 2,000, in close correspondence with sample sizes typically encountered in empirical applications of latent-variable methodology or factor analysis. As simple guidelines, 200 is regarded as a fair and very typical sample size for latent variable models (Comrey & Lee, 1992; Kline, 2011); 500 is classified as a good sample size (Comrey & Lee, 1992), typically encountered in online surveys (e.g., Nießen et al., 2019); and 2,000 is an excellent sample size (Comrey & Lee, 1992), typically encountered in large-scale assessment studies (e.g., Bilsky et al., 2011).

Factor correlation. For the scenarios with misspecified factor dimensionality, the correlation between the factors in the two-factor population model was either .30, .50, or .70. We chose these values to cover a wide range of factor correlations found in empirical studies (e.g., Groskurth et al., 2021; Kim et al., 2021; Lee & Cagle, 2017; Soto & John, 2017). As implied in the section about the magnitude of misspecification, one cannot demarcate the factor correlation from the misspecification. For the scenarios with misspecified (i.e., unmodeled) cross-loadings, we set the factor correlation between the two factors of the population model to either .00 (uncorrelated) or .30 (correlated), similar to factor correlations of empirical studies (e.g., Soto & John, 2017).⁴

Number of Simulation Samples

For each scenario (i.e., a combination of population model, analysis model, and characteristics), we drew 1,000 random samples. In total, we drew $N = 6,048,000$ samples.

⁴ Depending on the factor correlation, the two factors of the analysis model were either allowed to correlate or forced to be uncorrelated.

We had to re-simulate data whenever cell frequencies for any response option of any indicator resulted in fewer than five data points because DWLS/WLSMV can only estimate thresholds for response options that do contain observations. Collapsing data across incomplete (differently chunked or truncated) response distributions would undermine the idea of testing the effects of simulated scenarios. To prevent this from happening, we re-simulated improper data until all possible response options were covered in the simulated run. About 7% of all samples had to be re-simulated. About 2% of the models, we ran on theoretically suitable data, did not converge for other reasons. The final analysis contained GOFs for $N = 5,956,844$ converged models. We used R 3.6.3 (R Core Team, 2020) for all analyses. All R-packages we used are documented in our R code. Two packages were particularly central to our analyses: We generated data with MASS 7.3-53 (Venables & Ripley, 2002) and fit the analysis models to the data with lavaan 0.6-7 (Rosseel, 2012). For complete reproducibility, we set seeds within the R-code and monitored the R-package versions in use via renv 0.12.2 (Ushey, 2020). We did not preregister the design and analysis of this study. The full code is available on the Open Science Framework (OSF) at https://osf.io/e6kxa/?view_only=946034c00dee431897f67ca7ded58918.

Statistical Analyses

Computation of GOFs

We considered the following GOFs: χ^2 , χ^2/df , CFI, RMSEA, and SRMR. χ^2 is generally calculated by multiplying the fit function of the estimator with the sample size (i.e., $N-1$; Bollen, 1989). The lower χ^2 (or its ratio compared to the model degrees of freedom, χ^2/df), the better reproduces the model-implied the sample-based variance-covariance matrix. Lower values are bounded by zero.

CFI (Bentler, 1990) compares the χ^2 test statistic of the tested model (χ_t^2) to the one of a baseline model, usually the null model (χ_n^2) where all indicators are uncorrelated. In the null model, there are no latent variables that would explain variance shared among the indicators, only residual variances (see also Widaman & Thompson, 2003). CFI indicates how much better a model reproduces the sample-based variance-covariance matrix than a null model. Subtracting the expected values for perfectly fitting models—the degrees of freedom (df_t , df_n)—penalizes model complexity. CFI bounds are 0.00 (worst fit) and 1.00 (perfect fit).

$$CFI = 1 - \frac{\max(\chi_t^2 - df_t, 0)}{\max(\chi_n^2 - df_n, \chi_t^2 - df_t, 0)} \quad (1)$$

RMSEA (Steiger, 1990; see also F. F. Chen, 2007) takes the square root of the χ^2 test statistic of the tested model divided by its degrees of freedom. The closer RMSEA is to its lower bound of zero, the better the model fits. RMSEA has no upper bound.

$$RMSEA = \sqrt{\max\left(\frac{\chi^2 - df}{df(N-1)}, 0\right)} \quad (2)$$

SRMR (Bentler, 1995; Hu & Bentler, 1999) considers the average standardized residuals between sample-based and model-implied covariance matrices (s_{ij} = sample-based covariance; σ_{ij} = model-implied covariance; s_{ii} , s_{jj} = sample-based variance; p = number of indicators). SRMR values closer to zero reflect better model fit. SRMR values are bounded between 0.00 (perfect fit) and 1.00 (worst possible fit).

$$SRMR = \sqrt{\frac{\sum_{i=1}^p \sum_{j=1}^p ((s_{ij} - \sigma_{ij}) / (s_{ii} s_{jj}))^2}{p(p+1)/2}} \quad (3)$$

We took all GOFs from the lavaan output, except for the “manual” computation of χ^2/df .

434 ***Outcomes of Interest: The Sensitivity and Susceptibility of GOFs***

435 The outcomes of interest in our analyses were (1) the *sensitivity* of GOFs to model
436 misspecifications and (2) the *susceptibility* of GOFs to influences other than model
437 misspecification, such as the type of estimator or sample size. Though GOFs were
438 constructed to inform about model misspecifications, they may also be susceptible to data
439 and analysis characteristics in the absence (or presence) of any misspecification, which can
440 only be known through a simulation study.

441 We analyzed the sensitivity and susceptibility via descriptive and inferential statistics
442 along three main steps. First and foremost, we inspected the distributions of GOFs across the
443 different scenarios. Second, we looked at zero-order correlations (Kendall's tau-b to account
444 for ordinal level data) between the GOFs and simulation characteristics to get a first
445 impression of their sensitivity and susceptibility. Third, we looked at main and interaction
446 effects of characteristics on GOFs, including linear and quadratic terms, in a regression. The
447 multivariate regression complements the analysis of bivariate correlations, which collapses
448 across non-focal scenarios (i.e., those characteristics that are no part of the specific bivariate
449 correlation but vary in the data). It also conveys the size of any effects while preserving the
450 natural units of the variables (i.e., unstandardized beta-weights) to ease the interpretation.

451 However, the regression is still limited. Most importantly, we limited the regression
452 to only include two-way interactions for three reasons: First, we faced a technical restriction
453 regarding higher levels of interactions. We had to resort to the `biglm` function from the `biglm`
454 package in R (Lumley, 2013), which is explicitly designed to handle big data. However, the
455 `biglm` function is limited regarding the number of independent variables, including
456 interaction effects. As our comprehensive analyses comprised not only large data but also
457 many variables, these technical restrictions confined our analysis to two-way interactions. A

second reason was that the purpose of the regression is only to solidify, from a multivariate perspective, and quantify the various influences on GOFs that the descriptive statistics might suggest. A two-way interaction already suffices to show whether GOFs are subject to complex influences of various characteristics. Yet another reason why we focused on two-way interactions is to preserve straightforward interpretability. Whereas two-way interactions are readily interpretable, three- or even four-way interactions would complicate matters beyond a point where they add much value.

Fourth and finally, we visually inspected selected, large influences on GOFs. We selected those characteristics for visualization, which appeared to have a large (or complex) impact on GOFs in the preceding analyses. The visualization permits in-depth interpretation of higher-order interaction effects. The final visualization using the most relevant influences is key to our analysis.

Simulation Results

Sensitivity of GOFs: Descriptive Statistics

We first inspected how GOFs distribute across models with misspecifications in different scenarios (pooled across all simulation characteristics). Figure 3 compares the GOF distributions (i.e., χ^2 , χ^2/df , CFI, RMSEA, and SRMR) as violin plots for either correctly specified or misspecified models regarding factor dimensionality (i.e., one-factor analysis models for either a one-factor or two-factor population model). The Y-axis represents different degrees of severity of the misspecification, with the correctly specified model as a point of reference shown on top in green color (or light gray in grayscale). The X-axis represents the relevant range of values for each GOF. The black trace line vertically connects the GOF medians from different scenarios to reflect trends. We displayed each GOF in its

original metric and direction. Table A1 in the Additional File 1 of the Supplementary Online Material provides detailed descriptive statistics.

As expected, all GOFs signaled worse model fit with increasing magnitude of misspecification, as evident by medians shifting toward unfavorable fit values. That is, all GOFs detected the misspecification of factor dimensionality.

[please insert Figure 3 about here]

Similarly, Figure 4 shows the magnitude and proportion of cross-loadings in the population model that went unmodeled in the analysis model. We further split the figure into uncorrelated and correlated factor scenarios (factor correlation = .00 or .30) shown in Panels A and B, respectively. Table A2 in the Additional File 1 of the Supplementary Online Material contrasts the descriptive statistics for these scenarios.

We observed distinct influences of unmodeled cross-loadings on GOFs in uncorrelated and correlated factor scenarios. As expected, an increasing *magnitude* of misspecification entailed worse model fit, as evident by shifts of the GOF distributions toward more unfavorable values. For uncorrelated factors, an increasing *proportion* of misspecification also shifted the GOF distribution toward more unfavorable values. For correlated factors, higher proportions of unmodeled cross-loadings resulted in lower medians of each GOF distribution (as the zigzag trace line indicates). Consequently, as the number of indicators with unmodeled cross-loadings increased, GOFs tended to indicate *better*, not worse, model fit. Compare, for instance, the better fit GOFs indicated for 33% to 17% of indicators with unmodeled cross-loadings. We attend to this pattern in more detail in the Discussion.

[please insert Figure 4 about here]

Sensitivity and Susceptibility of GOFs: Bivariate Associations with Characteristics

Next, we quantified how GOFs responded to the different characteristics in correctly specified and misspecified models. We computed Kendall's tau-b as a measure of association between each simulation characteristic and GOF. To facilitate the readability of the following correlation tables, presented in a colored heatmap-style, we recoded GOFs such that lower values consistently represent worse model fit (i.e., χ^2 , χ^2/df , RMSEA, and SRMR were multiplied by -1). For increasing values of the simulated characteristics, positive correlations (colored in green) point to GOF values that indicated improving fit and negative correlations (colored in red or gray color when printed in black and white) point to diminishing fit. The stronger the absolute correlation coefficient, the more intense the color. Correlations of GOFs with the magnitude and proportion of misspecification help explore their sensitivity to misspecification. Correlations of GOFs with other characteristics alert to their unintended susceptibility in correctly specified or misspecified models.

Correctly Specified Models. Figure 5 shows the correlations for correctly specified one-factor models. GOFs and characteristics correlated moderately to strongly in many instances ($.20 \leq |\text{tau-b}| \leq .71$). With the DWLS estimator instead of the ML estimator, GOFs typically pointed to better model fit ($.22 \leq \text{tau-b} \leq .42$; except for SRMR with $\text{tau-b} = -.12$). As the number of indicators increased, χ^2 indicated less acceptable models ($\text{tau-b} = -.71$). Akin to χ^2 , SRMR was also susceptible to the number of indicators, suggesting worse model fit as models used more and more indicators ($\text{tau-b} = -.20$). SRMR was strongly influenced by sample size, and its values indicated better model fit when sample size increased ($\text{tau-b} =$

.63). SRMR also pointed to better model fit with increasing loading magnitudes ($\tau\text{-}b = .33$). Overall, Figure 5 demonstrates the extent of GOF susceptibility to data and analysis characteristics for *correctly* specified one-factor models.

[please insert Figure 5 about here]

Figure 6 shows the findings for two-factor models. Akin to GOFs of one-factor models, though to a lesser extent ($.12 \leq \tau\text{-}b \leq .21$), GOFs of two-factor models were related to the type of estimator, indicating better model fit when estimated with DWLS compared to ML, except for SRMR ($\tau\text{-}b = -.16$). As for GOFs of one-factor models, there were substantial correlations between χ^2 and the number of indicators ($\tau\text{-}b = -.71$), as well between SRMR and sample size ($\tau\text{-}b = .69$) or the number of indicators ($\tau\text{-}b = -.21$) for two-factor models. The correlation coefficients resulting from two-factor models were very similar to those from one-factor models (and the mathematical signs of the strongest coefficients identical), suggesting that the number of factors did not substantially impact GOFs from correctly specified models. We found the biggest difference between SRMR and loading magnitude for one- and two-factor models (.33 vs. .10, respectively).

[please insert Figure 6 about here]

Misspecified Models. Figure 7 shows the zero-order correlations between simulation characteristics and GOFs of analysis models that were misspecified regarding the factor dimensionality of the population models. All GOFs correlated substantially with the

magnitude of misspecification ($-.58 \leq \text{tau-b} \leq -.21$), as they should. GOFs indicated consistently worse fit with increasing magnitudes of misspecification.

Unfortunately for the applied researcher, GOFs also correlated with data and analysis characteristics other than misspecification. In fact, GOF susceptibility to other characteristics was extensive, sometimes exceeding their sensitivity to misspecification: All GOFs (except CFI) indicated substantially worse model fit as loading magnitudes increased ($-.74 \leq \text{tau-b} \leq -.52$). The χ^2 and χ^2/df increased with sample size (i.e., they have stronger power to detect misfit). They indicated worse fit with larger samples ($-.39 \leq \text{tau-b} \leq -.35$), as intended by their mathematical definition. The χ^2 also increased with the number of indicators (per definition and also true in our study, $\text{tau-b} = -.37$), against which the χ^2/df ratio is sufficiently guarded ($\text{tau-b} = .09$).

[please insert Figure 7 about here]

For models that were misspecified regarding cross-loadings (Figure 8), all GOFs correlated with the magnitude of misspecification (i.e., the size of unmodeled cross-loadings; $-.25 \leq \text{tau-b} \leq -.15$). Differently, all GOFs barely correlated with the proportion of misspecification ($.02 \leq |\text{tau-b}| \leq .06$). In sum, all GOFs were sensitive for the magnitude of misspecification. Still, they did not seem to be sensitive for the proportion of misspecification (which might be spurious due to a moderation effect of the factor correlation, see Figure 4).

Problematically, GOFs of models with unmodeled cross-loadings were susceptible to many characteristics. All else being equal, GOFs showed better fit when factors were correlated instead of uncorrelated ($.21 \leq \text{tau-b} \leq .51$). Further, GOFs suggested worse fit with

higher loading magnitudes ($-.39 \leq \text{tau-b} \leq -.22$), while only CFI pointed to better fit ($\text{tau-b} = .24$). χ^2 was strongly associated with the number of indicators ($\text{tau-b} = -.53$) and the sample size ($\text{tau-b} = -.36$). Also, χ^2/df and SRMR varied immensely with sample size, the former pointing to worse ($\text{tau-b} = -.48$) and the latter to better fit ($\text{tau-b} = .24$) with increasing sample size. GOF correlations with other characteristics were smaller than the correlations with the magnitude of misspecification.

[please insert Figure 8 about here]

Sensitivity and Susceptibility of GOFs: Multivariate Models with Joint Effects of Characteristics

Then, for all GOFs, we examined the joint effects of the characteristics combined, including their two-way interaction effects in a regression analysis using a least squares estimator (Lumley, 2013; Miller, 1992). We modeled quadratic effects in addition to linear ones for independent variables with more than two levels. We rescaled four independent variables (i.e., sample size, loading magnitude, magnitude and proportion of misspecification) before they entered the regression analysis: We divided the sample size by 100 to not dismiss seemingly small yet practically relevant regression coefficients (a unit change in sample size now reflects a change of 100 participants). Similarly, we multiplied the loading magnitude, magnitude of misspecification, and proportion of misspecification by factor 10 to prevent any substantial interpretation of seemingly large yet practically irrelevant regression coefficients. We mean-centered all non-binary independent variables to ease the subsequent interpretation of their interaction effects. As before, we recoded GOFs

so that lower values represented worse fit. For each GOF, we highlighted effects in black that were comparably larger than other effects in the regression.

[please insert Table 2 about here]

Correctly Specified Models. Several Table 2 columns summarize the findings for correctly specified models in terms of the direction of effects (not actual results or effect sizes), taken from the detailed regression results portrayed in Table A3 in the Additional File 2 of the Supplementary Online Material. We only included relatively large effects from the regression in Table A3 in the summary Table 2. Those large effects of single independent variables might be small on an absolute scale. Still, they stood out as strong relative to all other effects (and might even aggregate with seemingly small effects of other independent variables). We discuss those effects in the following and describe the findings from the multivariate regression context in relation to the bivariate correlational context. We start with describing converging findings, move over to misleading findings in the bivariate analysis as revealed by the multivariate analysis, and review findings of interaction effects that only multivariate analysis can uncover. Conclusively, we analyze the variance of GOFs explained by the included data and analysis characteristics (R^2).

Multivariate regression confirmed the findings from the zero-order correlations that even in correctly specified models, GOFs were relatively susceptible to various characteristics. Echoing the previous findings, χ^2 depended on the number of indicators, though the multivariate regression additionally revealed a large interaction effect for switching from ML to DWLS. Also, the sample size dependency of SRMR found in the bivariate correlation resurfaced in the multivariate regression.

The conditional effects of the various characteristics in the regression were often different from their bivariate associations. For example, the bivariate association of SRMR with the number of indicators totally vanished in the multivariate context.

The multivariate analysis showed that the bivariate associations also masked other, more complex interdependencies. Whereas bivariate correlations hardly suggested an influence of the response distribution (asymmetric vs. symmetric) on GOFs, the multivariate analyses revealed an impact. χ^2 , χ^2/df , and RMSEA (the latter especially in scenarios with one-factor models) suggested decreasing model fit for asymmetric instead of symmetric response distributions when using an ML estimator. However, when using MLR, DWLS, or WLSMV, the effect of the distribution vanished (in line with the—relatively negligible—bivariate correlation). In the bivariate analyses, GOFs had indicated better fit when using DWLS instead of ML; only SRMR had pointed to worse fit with DWLS. In the regression, by contrast, not only SRMR (especially in scenarios with two-factor models) but also CFI suggested worse fit with DWLS compared to ML. The overall positive zero-order correlation between CFI and DWLS may have been due to many small interaction effects that lead to a seemingly positive association in the aggregate. All other GOFs pointed to better model fit with DWLS than ML in the regression (though RMSEA only in scenarios with one-factor models). In the regression, CFI showed better fit with MLR compared to ML in scenarios with two-factor models. Further, regression models revealed interactions between the estimator (DWLS vs. ML) and other characteristics: With DWLS, increasing loading magnitudes suggested better fit according to χ^2 and χ^2/df , but not other GOFs. In the presence of correlated factors, DWLS indicated better model fit than with uncorrelated factors according to all tested GOFs.

The explained variance (R^2) in the multivariate regression quantifies the joint explanatory power of all simulated characteristics on GOFs, which should ideally be low (as GOFs are otherwise susceptible to those characteristics). We found R^2 to be consistently higher for correctly specified one-factor than two-factor models for all GOFs (see Table A3 in the Additional File 2 of the Supplementary Online Material). The characteristics of our simulation explained the largest share of variance in χ^2 and SRMR of correctly specified one- and two-factor models ($.815 \leq R^2 \leq .894$), meaning that χ^2 and SRMR depended most strongly on the various simulation characteristics. By comparison, all tested GOFs *derived* from χ^2 (i.e., χ^2/df , CFI, and RMSEA) were less influenced by data- and analysis-specific characteristics than χ^2 (or SRMR, for that matter), which in turn limited the GOF variability for correctly specified models that those characteristics might have explained. Overall, the effects of characteristics on GOFs in the multivariate analysis were rather small in absolute terms (though they might aggregate with seemingly small effects of other characteristics, see Table A3 in the Additional File 2 of the Supplementary Online Material).

Misspecified Models. The summary in Table 2 also shows columns for models with misspecified factor dimensionality or unmodeled cross-loadings. Table 2 includes all main and large interaction effects of model misspecifications and other characteristics based on the detailed regression results in Table A4 in the Additional File 2 of the Supplementary Online Material. We marked those effects as relatively large (or relevant), which were larger than the effects of the magnitude or, if applicable, proportion of misspecification. We discuss those effects in the following. We first describe the sensitivity of GOFs to the main effects of the magnitude or proportion of misspecification, followed by interaction effects between the misspecification and other characteristics. Third, we explore the susceptibility of GOFs to data and analysis characteristics. Fourth, we analyze the explained variance (R^2) of GOFs

taking all intended (i.e., magnitude and proportion of misspecification) and other characteristics together.

Echoing the correlational analysis, all GOFs were sensitive to the magnitude of misspecification in all regression models. They indicated worse fit as the size of the misspecification increased (i.e., more misspecification in factor dimensionality, higher unmodeled cross-loadings). A pattern that was masked in the zero-order correlations, but uncovered by the multivariate analysis, is that the sensitivity of GOFs to the proportion of misspecification behaved as expected. Increasing the proportion of cross-loadings in the population (but leaving them unmodeled in the analysis model) suggested decreasing model fit.

Crucially, the sensitivity of GOFs to misspecification depended on several other characteristics—a problem that the bivariate correlations could not unravel. This *differential* sensitivity of GOFs became evident through substantial two-way interaction effects of the magnitude and proportion of misspecification with the factor correlation (for all GOFs) and the type of estimator (for χ^2 and χ^2/df) in scenarios with unmodeled cross-loadings. We specifically draw the reader's attention to the interaction between the proportion of misspecification and the factor correlation. GOFs correctly suggested worse fit with a higher proportion of unmodeled cross-loadings if factors were uncorrelated. When factors were correlated, GOFs somewhat paradoxically suggested better fit. The factor correlation moderated the effect of the proportion of unmodeled cross-loadings on GOFs. The multivariate analysis confirmed a trend already evident in the GOF distributions in Figure 4 that the bivariate associations concealed.

Further, GOFs were susceptible to many data and analysis characteristics. Mirroring the correlational findings, as the loading magnitude increased, the multivariate regression

confirmed that most GOFs (i.e., χ^2 , χ^2/df , RMSEA, and SRMR; the latter especially in scenarios with misspecified factor dimensionality) typically indicated worse fit. Thus, low loadings concealed misfit. Only CFI pointed to better model fit with increasing loading magnitudes in scenarios with unmodeled cross-loadings (as already indicated by the bivariate correlations). Similar to the bivariate associations, the regression analyses showed that GOFs pointed to better fit in the presence of correlated rather than uncorrelated factors—an important aspect that, as indicated before, we will return to in the Discussion. We also observed a strong influence of the type of estimator on all GOFs (either in scenarios with misspecified factor dimensionality or unmodeled cross-loadings). The multivariate regression also revealed several substantial interactions with the type of estimator that the bivariate associations concealed: Most GOFs were not simply susceptible to the type of estimator but differentially so, depending on correlating factors (for χ^2 , χ^2/df , CFI, and RMSEA) or asymmetric response distributions (for χ^2/df in scenarios with misspecified factor dimensionality). CFI was also substantially susceptible to interactions of correlating factors and loading magnitude.

Fourth, the magnitude and proportion of misspecification and all other characteristics together explained up to 96% of the variation in GOFs (usually more than 62% in most scenarios; see Table A4 in the Additional File 2 of the Supplementary Online Material). As an exception to this rule, χ^2 and χ^2/df were not explained at all ($R^2 = .002$ at most) in scenarios with misspecified factor dimensionality. Thus, in scenarios with misspecified factor dimensionality, the R^2 pattern speaks favorably of χ^2 and the χ^2/df ratio as being immune to *systematic* influences of *data and analysis characteristics*, but also, and problematically so, as being insensitive to *model misspecification* (at least in our extensive simulation that manipulates several other characteristics).

Sensitivity and Susceptibility of GOFs: Selected, Visualized Effects of Characteristics

Finally, we move over to the most central part of the analyses: the visualization of selected main and interaction effects on GOFs. Our previous analyses identified substantial influences on GOFs. The sensitivity of GOFs to misspecification (i.e., unmodeled cross-loadings) was mediated by the factor correlation as identified through the descriptive statistics (Figure 4), bivariate correlations (Figure 8), and multivariate regression (Table 2). The regression further revealed a substantial susceptibility of all GOFs to different types of estimators and different loading magnitudes (for misspecified models). Influences on GOFs for correctly specified models had rather small effects in absolute terms, which was why we only selected effects on GOFs of misspecified models for an in-depth investigation. (Though those might aggregate with seemingly small effects of other characteristics, see Table A3 in the Additional File 2 of the Supplementary Online Material.) The visualization helps to illustrate the complex dependency of GOFs on these characteristics and the way they interact.

Figures 9–12 display those interactions via conditional median plots. The Y-axis shows the respective GOF and its values (original metric without altering the direction); the X-axis conveys the estimators or loading magnitudes. We disentangle the magnitude and, if applicable, proportion of misspecification by using differentially colored and, if applicable, shaped lines that connect medians for each scenario in the plot. For scenarios with unmodeled cross-loadings, we further split the figures by factor correlation.

As a general trend, GOFs were sensitive to misspecification. They correctly indicated worse fit with increasing magnitudes of misspecification across all estimators and loading magnitudes (Figures 9–12). As expected, a higher proportion of unmodeled cross-loadings also went along with worse fit if factors were uncorrelated. By contrast, a higher proportion

of unmodeled cross-loadings suggested better fit if factors were correlated (Figures 10 and 12; compare this to Figure 4; see also Discussion).

Next, we take a closer look at the susceptibility of GOFs to the type of estimator. A predominant trend was that GOFs were least sensitive to misspecification with DWLS compared to any other estimator (Figures 9 and 10), except for SRMR. However, this trend was moderated by factor correlation and capable of being completely reversed. In the presence of uncorrelated factors, GOFs (i.e., χ^2 , χ^2/df , and RMSEA) suggested worse model fit with DWLS than with other estimators (the only exception being CFI when using WLSMV; see Figure 10).

[please insert Figure 9 about here]

[please insert Figure 10 about here]

GOFs were not only susceptible to the type of estimator but also loading magnitude. GOFs became more sensitive to the magnitude and, if applicable, proportion of misspecification with higher loading magnitudes (Figures 11 and 12; though a higher proportion of misspecification resulted in more optimistic model fit in correlated-factor scenarios, as stated before). CFI was an exception to this pattern. Specifically, CFI showed a reverse or U-shaped relationship between loading magnitude and misspecification due to unmodeled cross-loadings, depending on the scenarios one looks at. Put differently, CFI pointed to better fit with increasing loading magnitudes in most scenarios of unmodeled cross-loadings (Panel A and B in Figure 12). Only at a large proportion of unmodeled cross-

loadings (33%) and correlated factors (Panel B in Figure 12), CFI pointed to better fit with low and high magnitude while medium magnitudes showed worse fit.

[please insert Figure 11 about here]

[please insert Figure 12 about here]

Discussion

GOFs were designed to detect model misspecifications and help judge the tenability of latent variable models (e.g., Hu & Bentler, 1999). But how well do GOFs fulfill this purpose? We approached this question by conducting the most comprehensive simulation study to date on the *sensitivity* of GOFs to model misspecification in CFA models and their *susceptibility* to other data and analysis characteristics. Crucially, data and analysis characteristics other than misspecifications should *not* influence GOFs, lest judgments of model fit may become seriously biased.

Four main insights emerge from our analysis of more than 6×10^6 simulated datasets. First, unsurprisingly, GOFs were sensitive to misspecifications of both factor dimensionality and cross-loadings: All GOFs correctly indicated worse fit as the degree of misspecified factor dimensionality increased (i.e., the correlation between two factors that were incorrectly modeled as a single factor decreased). GOFs also correctly indicated worse model fit as the magnitude and proportion of unmodeled cross-loadings grew (but only when the factors in the model were uncorrelated).

Second, the sensitivity of GOFs to model misspecification was not the same across all scenarios but varied considerably depending on several other data and analysis

characteristics (especially the type of estimator and correlating factors). Most intrusively, when factors were correlated, GOFs suggested better (rather than worse) model fit as the proportion of unmodeled cross-loadings grew. It may come as a surprise to applied researchers that the ability of GOFs to detect misspecification depends so strongly on the correlation of factors. In hindsight, this finding is plausible: Fitting a correlated two-factor analysis model which ignores substantial cross-loadings present in the population model implies a different meaning and orientation of the two factors in the variable space. The factor with the indicators whose cross-loadings went unmodeled reflects a blend of both factors, such that the factor correlation increases. Concomitantly, the estimated factor loadings of indicators with unmodeled cross-loadings are higher than those of correctly modeled indicators. Therefore, a model with correlated factors and substantial cross-loadings that go unmodeled (i.e., are assumed to be zero) accounts for the cross-loadings through other model parameters (i.e., the factor correlation and factor loadings), resulting in seemingly good model fit despite misspecification. A strong correlation between the estimated factor correlation and the proportion of unmodeled cross-loadings corroborated this interpretation ($\tau\text{-}b = .54$). Phrased differently, the estimated factor correlations were higher than the induced one (i.e., factor correlation of .30 in the population model) and increased when the proportion of unmodeled cross-loadings increased (0%, 17%, 33% unmodeled cross-loadings: median of estimated factor correlations = .30, .46, .54, respectively).

Third, GOFs showed considerable susceptibility to data and analysis characteristics of correctly specified and misspecified models. *All* GOFs analyzed here were susceptible to influences other than model misspecification (especially influences of the type of estimator, loading magnitude, and factor correlation). The susceptibility of GOFs to data and analysis

characteristics differed between correctly specified models, misspecified models, and different kinds of misspecified models. It is, thus, even more complex than previously assumed. Most interestingly, former studies (Xia & Yang, 2019) found that DWLS-based GOFs (i.e., χ^2 , CFI, and RMSEA) depicted misspecified models more favorably than ML-based GOFs did. Our results shed new light on that finding and revealed an interaction with the factor correlation when cross-loadings went unmodeled. DWLS-based GOFs pointed to better fit than ML-based ones with correlated factors; the effect was reversed with uncorrelated factors.

Fourth, some known influences on GOFs were not as substantial as previously assumed when considering multiple contributing factors in a multivariate analysis. For instance, Xia and Yang (2018) found that asymmetric response distributions lead to more optimistic model fit evaluations for DWLS-/WLSMV-based GOFs (i.e., χ^2 , χ^2/df , CFI, and RMSEA) for misspecified models than do symmetric ones (which are required by the assumption of normality). Though we replicated this principal finding, our interaction effect between DLWS/WLSMV and asymmetry was small relative to other effects in our multivariate analysis. To compare our main and interaction effects with previous findings, we refer the reader to Table A5 in the Additional File 2 of the Supplementary Online Material. This finding highlights that considering the interdependencies among the different influences on GOFs is essential to fully understand the differential sensitivity and susceptibility to extraneous influences on GOFs.

We scrutinized the influences on GOFs through different lenses, including a visual inspection of descriptive statistics but also multivariate regression models with quadratic and interaction terms. Most simulation studies have presented only descriptive statistics (e.g., Moshagen & Auerswald, 2018; Nye & Drasgow, 2011; Reußner, 2019) or invoked effect

size measures such as η^2 (sometimes also including interactions, e.g., Beauducel & Herzberg, 2006; Fan & Sivo, 2007; Hu & Bentler, 1998). Our multivariate analysis reported the effects of each characteristic controlling simultaneous influences of all others. It further included quadratic and interaction terms, which produced unique insights into the sensitivity and susceptibility of GOFs that simpler analysis techniques cannot reveal. We limited ourselves to quadratic effects and two-way interactions for technical reasons and to keep our already complex analysis as simple as possible. The descriptive statistics and conditional median plots suggested that there might be even more complex interactions (e.g., four-way interactions, such as between the magnitude and proportion of misspecification, loading magnitude, and factor correlation). However, the substantial number of two-way interactions we found already suffice to demonstrate the key issue with great clarity: GOFs respond to various data and analysis characteristics in often complex and hard-to-predict ways.

As outlined throughout the paper, we investigated the sensitivity and susceptibility of GOFs for many combinations of data/analysis characteristics and types of misspecification, considerably extending the scope of previous simulation studies. Still, even our enlarged simulations could not cover all (potentially relevant) data and analysis characteristics or types of misspecification. An important limitation to be aware of is our self-imposed restriction to CFA models (see Garrido et al., 2016, for an extensive simulation about fit in exploratory structural equation models). Further, we limited ourselves to two types of misspecification (i.e., misspecification due to factor dimensionality and misspecification due to unmodeled cross-loadings), being fully aware that there are other types of misspecification that regularly occur in empirical settings (such as unmodeled residual covariances; see Podsakoff et al., 2003). In addition to the influences we documented here,

such characteristics are likely to impact GOFs (e.g., Savalei, 2012; Shi et al., 2019; Shi, Maydeu-Olivares, & DiStefano, 2018; Shi & Maydeu-Olivares, 2020).

Implications

We acknowledge that the sheer number of results from our simulation can be daunting. However, together these results convey a clear and straightforward message. (1) The sensitivity of GOFs to model misspecifications varies greatly across analysis scenarios. (2) GOFs are susceptible to various data and analysis characteristics, meaning that they reflect characteristics other than the magnitude and proportion of model misspecification. The influence of data and analysis characteristics on GOFs is complex in empirical settings.

These findings imply that one must not blindly trust the values of GOFs as if they exclusively reflected (mis)fit, let alone rigidly apply fixed cutoffs for model evaluation. We believe this important insight should be internalized by all (applied) researchers and included in statistics and methods curricula dealing with model evaluation. Moreover, while we understand that our findings may sound pessimistic and leave some readers wondering how to approach model evaluation in the future, we are convinced that the fundamental issues with GOFs that we and others before us (e.g., Marsh et al., 2004; McNeish & Wolf, 2021) identified have a silver lining: They can encourage researchers to think more deeply about the appropriateness of fixed cutoffs for GOFs and explore alternative procedures that will ultimately lead to more valid judgments about whether a model can be accepted.

Below, we first expand on the problem with fixed cutoffs for GOFs that springs from the differential sensitivity and susceptibility of GOFs to various data and analysis characteristics. Following this, we outline several promising avenues for model evaluations that do not rely on problematic fixed cutoffs.

884 (Fixed Cutoffs For) GOFs Are More Problematic Than Commonly Assumed

885 Considering the findings of our simulation, how solid as a basis for evaluating model
886 fit are fixed cutoffs for GOFs? Our results suggest that relying on the same fixed cutoffs to
887 judge model fit in real data applications can be highly problematic and misleading in many
888 settings. Thanks to the breadth of scenarios we studied, we can now further illustrate and
889 quantify this problem. To do so, we estimated the frequency distribution of GOFs for
890 correctly specified models separately for each simulation scenario. The 95% quantile (for χ^2 ,
891 χ^2/df , RMSEA, and SRMR; 5% quantile for CFI) of each frequency distribution corresponds
892 to a 5% probability of concluding that a model is misspecified when it is in fact correctly
893 specified (i.e., 5% Type I error rate). We can use those quantiles as suitable cutoffs for
894 GOFs. Additional File 3 of the Supplementary Online Material (Tables A6–A10) shows the
895 tabulated quantiles.

896 Researchers often take CFI values above .950 to indicate good model fit (Hu &
897 Bentler, 1999). This heuristic might be sufficiently accurate under some but certainly not
898 under all circumstances. Especially low loading magnitudes undermine the nominal Type I
899 error rate when a cutoff of $CFI > .950$ is used. In some scenarios, *much more lenient* values
900 than .950 indeed maintain a 5% error rate. For example, a cutoff as low as $CFI = .813$ is fully
901 appropriate to demarcate models that fit the data from those that do not fit for a one-factor
902 model estimated with ML at a sample size of $N = 200$, with loadings of .40 for six indicators
903 and seven response options, in the presence of asymmetric data. In other scenarios, such as
904 in the presence of high loadings, maintaining a 5% error rate requires *much stricter* values
905 than .950 (e.g., a cutoff of .979 results with loadings of .80 in an otherwise identical setting).
906 To be very clear, accepting (or rejecting) models under various scenarios at a fixed cutoff
907 (.950) does not effectively control the Type I error rate. Fixed cutoffs cannot do justice to

every possible setting. Consequently, we strongly discourage researchers from inferring the tenability of a model based on the conventional, fixed cutoffs.

These examples highlight two caveats about fixed cutoffs, such as those by Hu and Bentler (1999), that have guided applied researchers' model evaluations for more than two decades. Using cutoffs under scenarios not covered in the initial simulation studies is highly problematic. This pertains, for instance, to testing models with low compared to high factor loadings. For model evaluations through GOFs to be valid, researchers need to consider their specific data and analysis characteristics. In this regard, our findings reinforce previous warnings against overgeneralizing cutoffs, including those by Hu and Bentler (1999) in their original publication suggesting the canonical cutoffs (see also Marsh et al., 2004; McNeish & Wolf, 2021; Nye & Drasgow, 2011).

Moving from Fixed to Tailored Cutoffs is the Way Forward

Where does this leave applied researchers who seek to evaluate the fit of their model? We recommend that researchers take three steps. First, researchers should consider and test alternative models to learn more about potentially better-suited models. Second, they need to inspect local (mis)fit, for instance via the residual matrix and modification indices, to investigate whether a model is probably correctly specified or misspecified (see Pornprasertmanit, 2014, for a sophisticated strategy to evaluate local fit). Third, and most promisingly, researchers should inspect global fit not via fixed but via *tailored* (sometimes called "dynamic"; McNeish & Wolf, 2021) cutoffs for GOFs to evaluate the overall model fit free from bias, including any entailed misfit. Whereas considering alternative models and inspecting local fit are time-honored strategies, tailored cutoffs are a much more recent approach that, we believe, holds great promise and offers a much-needed remedy for the issues with GOFs identified in our present simulation. We believe applied research needs to

move toward tailored cutoffs for GOFs that take into account the specific data and analysis characteristics. However, tailored cutoffs are a recent development and not yet widely used. To foster the much-needed move toward tailored cutoffs, we outline the procedures of evaluating tailored cutoffs in more detail here. We hope to encourage more researchers to consider this emerging strategy. We also provide practical examples and R code illustrating how tailored cutoffs can be implemented.

Tailoring cutoffs for GOFs to the specific data and analysis characteristics can be achieved in different ways. One strategy, which we call the table-based approach, is to consider tables from simulation studies with scenario-specific cutoffs, such as Tables A6 to A10 in the Additional File 3 of the Supplementary Online Material. These tables contain cutoffs for combinations of data and analysis characteristics. They were created to read out the cutoff that can maintain error rates at the desired level in one's specific empirical setting (i.e., accounting for the data and analysis characteristics). This strategy is easy to apply and reminiscent of looking up critical values of, say, *z*-scores or *t*-statistics. One merely selects cutoffs for GOFs from the simulation scenario that most closely resembles one's own empirical data and analysis characteristics. For example, for a one-factor model with six indicators with five response options, factor loadings around .60, and a symmetric response distribution estimated with WLSMV in a sample of 200 respondents, one would reject the tested model if the χ^2/df ratio is larger than 1.918, CFI is smaller than .972, RMSEA is larger than .068, or SRMR is larger than .048. However, the table-based approach is somewhat limited: If the simulation scenario is too dissimilar from one's actual data and analysis characteristics, cutoffs may not be valid in the empirical setting at hand.

Two other strategies to arrive at tailored cutoffs are superior to the simplistic first strategy. They can be broadly summarized as regression-/equation-based (e.g., Nye &

956 Drasgow, 2011) and simulation-based approaches (e.g., McNeish & Wolf, 2021; Millsap,
957 2013; Pornprasertmanit, 2014).

958 In the regression-/equation-based approach⁵, a regression formula predicts tailored
959 cutoffs (Nye & Drasgow, 2011). The formula originates from a single simulation study
960 containing information about how data and analysis characteristics influence GOFs. Users
961 plug characteristics of their own empirical setting into the formula to obtain cutoffs.

962 To exemplify the regression-/equation-based approach, we derived a regression
963 equation for tailored cutoffs based on the results of our present simulation. The procedure
964 was as follows: We took the cutoffs of Tables A6 to A10 in the Additional File 3 of the
965 Supplementary Online Material as dependent variables and regressed them on all data and
966 analysis characteristics, as well as their quadratic terms and two-way interactions. The data
967 and analysis characteristics, as well as their quadratic terms and two-way interactions,
968 explained a large share of the variation in cutoffs for GOFs ($R^2 \geq .810$). We saved the
969 regression coefficients in Table 3. To arrive at appropriate cutoffs for one's own empirical
970 problem, one plugs their empirical data and analysis characteristics into the regression

⁵ One can also loosely subsume another approach under the regression-/equation-based category: Researchers can derive tailored cutoffs by relying on statistical assumptions of the χ^2 distribution with and without misspecification (Moshagen & Erdfelder, 2016). Except for the distribution of χ^2 , GOF distributions are unknown. As many GOFs (e.g., RMSEA) incorporate the χ^2 , one can infer their distribution with and without model misspecification from the χ^2 distribution. A certain quantile of the GOF distribution without misspecification may serve as a cutoff.

equation using the coefficients from Table 3. We included a user-friendly R script for this purpose in the Additional File 4 of the Supplementary Online Material. In principle, the regression equation allows researchers to derive appropriate cutoffs even if their empirical data and analysis characteristics do not perfectly match the ones from the simulation studies.

This approach constitutes a clear advancement over the status quo of rigidly using fixed cutoffs, whatever the preferred heuristic for a GOF is. Further, it is more general than the simplistic table-based approach described first. It is also highly efficient because no new simulation must be carried out (as in the simulation-based approach described next).

However, the potential downside is that the starting point is still a single simulation study that—no matter how comprehensive—can never cover all possible real-world settings.

Although extrapolation is possible in principle, researchers should only use the regression equation for tailored cutoffs when empirical settings do not strongly deviate from the simulation scenarios.

[please insert Table 3 about here]

If empirical settings strongly deviate from simulation scenarios, cutoffs neither from cutoff tables nor from regression equations should be used. Instead, one may adopt the third approach and conduct a small-scale, scenario-specific simulation to investigate the behavior of GOFs as recently suggested by McNeish and Wolf (2021; for similar earlier work, see Millsap, 2007, 2013; Niemand & Mai, 2018; Pornprasertmanit, 2014; for nested models see Pornprasertmanit et al., 2013). Before initializing the simulation, researchers define analysis and population models. Then, they simulate data from the population model (via a Monte Carlo simulation, similar to what we did in the present paper), fit the analysis model to the

data, and record the GOFs. Similar to our tables in the Additional File 3 of the Supplementary Online Material, researchers then extract cutoffs from the resulting GOF distributions. The analysis model can equal (or approximately equal; see Millsap, 2007, 2013; Pornprasertmanit, 2014) the population model, which corresponds to a correctly specified model. Cutoffs derived from the GOF distribution of correctly specified models control the Type I error rate (as implemented in the approaches of McNeish & Wolf, 2021; Millsap, 2007, 2013; Niemand & Mai, 2018; Pornprasertmanit, 2014). Including a misspecified model (i.e., where the analysis model differs considerably from the population model) allows to control the Type II error rate in the derivation of tailored cutoffs (as implemented in the approaches of McNeish & Wolf, 2021; Pornprasertmanit, 2014).

Choosing simulation characteristics (e.g., analysis model, sample size, estimator) similar to those of the empirical setting of interest is the gold standard to arrive at tailored cutoffs. By simulating data, cutoffs can be tailored to the empirical setting at hand. However, the flexibility of the simulation-based approach may not always be a merit but also a difficulty. The simulation-based approach demands specific knowledge about defining population and analysis models and running and analyzing simulations. Automated solutions (i.e., shiny apps) can considerably ease the process (e.g., McNeish & Wolf, 2021; Niemand & Mai, 2018).

In sum, the table-, regression-/equation-, and simulation-based approaches are three alternative ways to arrive at tailored cutoffs for model evaluation. Although these procedures are somewhat more involved than judging model fit against fixed cutoffs for GOFs, we hope that our simulation results have convinced the reader of the urgency of phasing out fixed cutoffs in favor of a more valid tailored approach.

Conclusion

GOFs were designed to detect model misspecifications and support the evaluation of model fit. However, our simulation study highlights two fundamental problems with GOFs. First, GOFs reflect not only model misspecification but are susceptible to a range of data and analysis characteristics (other than model misspecification). Second, the sensitivity of GOFs to model misspecifications also depends on such characteristics. In this regard, a particularly impressive (and alarming) finding was the strong dependence of absolute GOF values and their misspecification sensitivity to the factor correlation, magnitude of factor loadings, and type of estimator. Such characteristics are irrelevant from the applied researcher's point of view for judging model fit or identifying misspecifications. Hence, they should ideally have no bearing at all on GOFs. However, our findings converge with—and expand—previous smaller-scale simulations suggesting that a range of characteristics other than misspecifications influence absolute GOF values.

The pattern of associations between those characteristics and GOFs is complex, as quadratic and interaction effects attest; it varies for different GOFs and is hard to predict for specific constellations. This complexity means that simple modifications, such as adding or subtracting a constant from cutoff values, cannot come at a rescue. The problem lies with fixed cutoffs for GOFs *as such*. Fixed cutoffs cannot do justice to all combinations of data and analysis characteristics that researchers encounter in applied settings.

We believe that our findings make it abundantly clear that the conventional practice of relying on fixed cutoffs for GOFs is far more problematic than commonly assumed. Even though previous simulations had already raised some of the issues highlighted in our study, these issues appear not to be widely recognized by applied researchers. Even though Hu and Bentler (1999) themselves already cautioned researchers to execute some discretion when

using their cutoffs (see also McNeish & Wolf, 2021), applied researchers continue to rely on these cutoffs even in settings that differ markedly from the scenarios covered by Hu and Bentler (1999) and related studies such as those by Reußner (2019) or Rutkowski and Svetina (2014). More than 20 years later, our comprehensive simulation resonates with their initial warnings and brings several additional issues to light. Consequently, we urge researchers to be wary of the problems with fixed cutoffs henceforth.

We recommend researchers to routinely adopt the time-honored strategies of inspecting (and reporting) local fit and comparing alternative models instead of relying exclusively on GOFs. Methodologists have long advocated these effective strategies, but these are far from being universally applied in published research. Overall, however, we believe that the field needs to move away from relying on fixed cutoffs and toward cutoffs tailored to the specific data and analysis characteristics at hand (e.g., McNeish & Wolf, 2021). Tailored cutoffs offer an appropriate response to the susceptibility of GOFs and the ensuing lack of validity of fixed cutoffs. To contribute to a much-needed shift toward tailored cutoffs, we discussed three emerging strategies for how tailored cutoffs can be implemented and pointed to ongoing work that aims to improve these strategies further. We hope that our simulation results will encourage researchers to embark on this path, ultimately resulting in valid and replicable research.

Additional Files

1061

1062 Additional File 1: Descriptive Statistics of GOFs

1063 Additional File 2: Main and Interaction Effects on GOFs

1064 Additional File 3: 5%/95% Quantiles of GOF Distributions Resulting from Correctly

1065 Specified Models

1066 Additional File 4: Code to Derive Tailored Cutoffs via a Regression Equation in R

Abbreviations

1067

1068 CFA: confirmatory factor analysis

1069 CFI: comparative fit index

1070 df: degrees of freedom

1071 DWLS: diagonally weighted least squares

1072 GOF: goodness-of-fit indices

1073 ML: maximum likelihood

1074 MLR: robust maximum likelihood

1075 RMSEA: root mean square error of approximation

1076 SRMR: standardized root mean square residual

1077 WLSMV: diagonally weighted least squares mean and variance adjusted

1078

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Ethics Approval and Consent to Participate

Not applicable

Consent for Publication

Not applicable

Availability of Data and Materials

The code to reproduce the simulation, analysis, and results of this article is available on the
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Competing Interests

We have no competing interests to disclose.

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1103 **Authors' Contributions**

1104 **Katharina Groskurth:** Conceptualization, Methodology, Software, Validation, Formal

1105 Analysis, Investigation, Data Curation, Writing – Original Draft, Visualization.

1106 **Matthias Bluemke:** Conceptualization, Methodology, Writing – Review & Editing,

1107 Supervision.

1108 **Clemens M. Lechner:** Conceptualization, Methodology, Validation, Resources, Writing –

1109 Review & Editing, Visualization, Supervision.

1110

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Tables

Table 1*Simulation Scenarios*

	Realization			
Characteristic	For all Population Models: Factor Variances = 1, Factor Means = 0, Residual Variances = $1 - (Var(F1) \times \lambda_{F1}^2 + Var(F2) \times \lambda_{F2}^2 + 2 \times \lambda_{F1} \times \lambda_{F2} \times Cov(F1, F2))$ Replications = 1,000			
	(1)		(2)	
	Factor Dimensionality		Cross-Loadings	
Population Model	One-Factor Model	Two-Factor Model	Two-Factor Model	Two-Factor Model with Cross-Loadings
Analysis Model	One-Factor Model	One-Factor Model	Two-Factor Model	Two-Factor Model without Cross-Loadings
Specification	Correct	Misspecified	Correct	Misspecified
Magnitude of Misspecification	.00	.30, .50, .70	.00	.20, .30
Proportion of Misspecification	0.00 (= 0%)	1.00 (= 100%)	0.00 (= 0%)	0.17, 0.33 (= 17%, 33%)
Estimator	ML, MLR, DWLS, WLSMV	ML, MLR, DWLS, WLSMV	ML, MLR, DWLS, WLSMV	ML, MLR, DWLS, WLSMV
Number of Indicators	6, 12	6, 12	6, 12	6, 12
Response Options	3, 5, 7	3, 5, 7	3, 5, 7	3, 5, 7
Distribution of Responses	Symmetric, Asymmetric	Symmetric, Asymmetric	Symmetric, Asymmetric	Symmetric, Asymmetric
Loading Magnitude	.40, .60, .80	.40, .60, .80	.40, .60, .80	.40, .60, .80
Sample Size	200, 500, 2,000	200, 500, 2,000	200, 500, 2,000	200, 500, 2,000
Factor Correlation	1.00	Equals Complement of Magnitude of Misspecification	.00, .30	.00, .30
Total Number of Scenarios	432 (<i>n</i> = 432,000)	1,296 (<i>n</i> = 648,000)	864 (<i>n</i> = 864,000)	3,456 (<i>n</i> = 3,456,000)
	1,728 (<i>n</i> = 1,728,000)		4,320 (<i>n</i> = 4,320,000)	
	6,048 (<i>N</i> = 6,048,000)			
	7% Non-Convergence			
2% (Final <i>N</i> = 5,956,844)				

1350 *Note.* F1 = first factor; F2 = second factor; Var = variance; λ = factor loading; Cov =
1351 covariance; N = total number of datasets, n = subset of datasets.

1352 **Table 2**1353 *Summary of the Sensitivities and Susceptibilities of GOFs to Model Misspecification and Other Influences*

Independent variables	Dependent variables									
	χ^2		χ^2/df		CFI		RMSEA		SRMR	
	correct (1F/2F)	misspecified (Dim./Load.)	correct (1F/2F)	misspecified (Dim./Load.)	correct (1F/2F)	misspecified (Dim./Load.)	correct (1F/2F)	misspecified (Dim./Load.)	correct (1F/2F)	misspecified (Dim./Load.)
Main effects										
Misspecification magnitude		–		–		–		–		–
Misspecification proportion ^a		–		–		–		–		–
Estimator (Reference ML)										
MLR		– (Dim.)		– (Dim.)	+	(2F)		– (Dim.)		
DWLS	+	– (Load.)	+	– (Load.)	–	+ / –	+	(1F)	– (2F)	– (Load.)
WLSMV		– (Load.)		– (Load.)		– (Load.)		– (Load.)		
Number of indicators	–									
Response options										
Asymmetric (Reference symmetric)	–		–				– (1F)			
Loading magnitude		–		–		+	(Load.)	–		– (Dim.)
Sample size									+	
Correlated factors (.30, Reference .00) ^a		+		+		+		+		+
Large two-way interaction effects										
Misspecification magnitude ×										
DWLS		– (Load.)		– (Load.)						
WLSMV		– (Load.)								
Correlated factors ^a		+		+		+		+		+
Misspecification proportion ^a ×										
DWLS		–		–						
Correlated factors ^a		+		+		+		+		+
MLR ×										
Asymmetric	+		+	– (Dim.)			+	(1F)		

Independent variables	Dependent variables									
	χ^2		χ^2/df		CFI		RMSEA		SRMR	
	correct (1F/2F)	misspecified (Dim./Load.)	correct (1F/2F)	misspecified (Dim./Load.)	correct (1F/2F)	misspecified (Dim./Load.)	correct (1F/2F)	misspecified (Dim./Load.)	correct (1F/2F)	misspecified (Dim./Load.)
DWLS×										
Number of indicators	+									
Asymmetric	+		+				+	(1F)		
Loading magnitude	+		+							
Correlated factors ^a	+	+	+	+	+	+	+	+	+	
WLSMV×										
Asymmetric	+		+				+	(1F)		
Correlated factors ^a						+				
Loading magnitude×										
Correlated factors ^a						—				

1354 *Note.* Having recoded GOFs so that lower values represent worse fit (i.e., χ^2 , χ^2/df , RMSEA, and SRMR were multiplied by -1), “+” points to

1355 improving fit and “—” to worse fit with the increase of a characteristic. Blank gray cells indicate that the scenario was not/could not be tested in

1356 our simulation. Blank white cells indicate that we found no (relatively large) effect. Brackets indicate effects that apply only to certain scenarios

1357 (printed in light gray color). If we found differently large effects per type of correctly specified or misspecified model, we separated the effects

1358 with a slash (1F/2F and Dim./Load., respectively). 1F = One-factor CFA. 2F = Two-factor CFA. Correct = correctly specified models.

1359 Misspecified = misspecified models. Dim. = Misspecified factor dimensionality. Load. = Unmodeled cross-loadings. MLR = MLR (Yuan &

1360 Bentler, 2000). ^aOnly for GOFs from two-dimensional models (2F) and models with unmodeled cross-loadings (Load.). The multiplication sign

1361 (×) indicates interaction terms. SRMR is only available for comparing ML and DWLS because the SRMR point estimates are identical for

1362 models with ML and MLR estimators and models with DWLS and WLSMV estimators (Maydeu-Olivares et al., 2018). We based the summary

1363 table on the findings from Table A3 for correctly specified models and Table A4 for misspecified models in the Additional File 2 from the
1364 Supplementary Online Material. The table includes all main effects and large two-way interaction effects.

Table 3*Regression Equations to Derive Tailored Cutoffs*

Independent variables	Dependent variable				
	χ^2	χ^2/df	CFI	RMSEA	SRMR
Intercept	-23.94201	3.28519	-0.53129	0.13285	0.05279
Main effects					
Estimator (Reference: ML)					
MLR	6.72418	0.45189	-0.21041	0.01536	—
DWLS	5.84976	-0.68404	0.19662	-0.03062	0.03774
WLSMV	-4.68805	-0.27096	0.06079	-0.00865	—
Number of indicators	11.08965	-0.04753	0.04016	-0.00235	0.00278
Response options	-7.16670	-0.35058	0.12387	-0.00896	-0.00963
Response options^2	0.72250	0.03496	-0.00936	0.00098	0.00084
Asymmetric	-0.27294	0.02331	-0.04904	-0.00024	-0.00115
Loading magnitude	-25.73792	-3.58376	4.12967	-0.08865	0.02653
Loading magnitude^2	20.41717	2.96247	-2.75074	0.05766	-0.09506
Sample size	0.00906	0.45022	2.27580	-0.12606	-0.05619
Sample size^2	1.20211	-0.15723	-0.82698	0.04331	0.01882
Number of factors	-12.26618	-0.19792	-0.32211	-0.00594	0.01323
Two-way interaction effects					
Estimator (Reference: ML)					
MLR×Number of indicators	-0.49485	-0.01090	0.00247	-0.00041	—
MLR×Response options	0.17085	0.00216	0.00384	0.00005	—
MLR×Response options^2	-0.02131	-0.00052	-0.00024	-0.00001	—
MLR×Asymmetric	-2.71568	-0.08311	-0.00135	-0.00225	—
MLR×Loading magnitude	-7.76460	-0.99175	0.45378	-0.03246	—
MLR×Loading magnitude^2	-2.61117	0.42949	-0.31994	0.01556	—
MLR×Sample size	-3.93101	-0.26550	0.09707	-0.00768	—
MLR×Sample size^2	1.45709	0.09907	-0.03794	0.00311	—
MLR×Number of factors	2.71283	0.11781	-0.00868	0.00304	—
DWLS×Number of indicators	-2.43747	0.00544	0.00158	-0.00038	-0.00022
DWLS×Response options	-0.39327	-0.02550	-0.00440	-0.00033	-0.00758
DWLS×Response options^2	0.02110	0.00195	0.00034	0.00003	0.00058
DWLS×Asymmetric	-3.01669	-0.09613	0.00452	-0.00244	0.00140
DWLS×Loading magnitude	-41.99689	-1.36226	-0.30944	-0.05998	-0.00280
DWLS×Loading magnitude^2	16.73726	0.48895	0.18350	0.02118	-0.00311
DWLS×Sample size	-2.10846	-0.11430	-0.11629	0.02896	-0.02165
DWLS×Sample size^2	0.75628	0.04419	0.04250	-0.00982	0.00756
DWLS×Number of factors	16.86537	0.64662	-0.01075	0.02281	0.00330
WLSMV×Number of indicators	-0.60239	-0.00413	0.00097	-0.00029	—
WLSMV×Response options	0.63654	0.01440	-0.00270	0.00054	—
WLSMV×Response options^2	-0.05539	-0.00115	0.00022	-0.00004	—
WLSMV×Asymmetric	-2.91980	-0.09484	0.00368	-0.00256	—
WLSMV×Loading magnitude	10.29574	0.24493	-0.06415	0.00577	—
WLSMV×Loading magnitude^2	-15.70961	-0.45035	0.03405	-0.01194	—
WLSMV×Sample size	3.01133	0.05021	-0.04314	0.00682	—
WLSMV×Sample size^2	-1.16888	-0.01938	0.01545	-0.00250	—
WLSMV×Number of factors	3.90897	0.15706	-0.00697	0.00452	—

Independent variables	Dependent variable				
	χ^2	χ^2/df	CFI	RMSEA	SRMR
Number of indicators×					
Response options	-0.25997	-0.00776	0.00002	-0.00033	-0.00019
Response options^2	0.02789	0.00081	-0.00003	0.00004	0.00002
Asymmetric	0.17890	0.00040	0.00034	0.00002	0.00003
Loading magnitude	-4.80064	-0.04388	-0.10488	-0.00698	-0.00316
Loading magnitude^2	3.83154	0.04484	0.07017	0.00652	0.00190
Sample size	-1.04664	0.00016	-0.01404	0.00655	-0.00160
Sample size^2	0.38895	0.00157	0.00500	-0.00224	0.00058
Number of factors	0.64889	-0.01164	0.00234	-0.00030	0.00003
Response options×					
Asymmetric	0.47743	0.01356	-0.00319	0.00043	0.00061
Loading magnitude	22.43204	1.53987	-0.33800	0.04504	0.01794
Loading magnitude^2	-19.13312	-1.33866	0.23297	-0.03818	-0.01639
Sample size	2.42094	-0.20111	-0.00951	-0.00561	0.01125
Sample size^2	-1.16974	0.07428	0.00109	0.00208	-0.00388
Number of factors	1.18404	0.04887	0.00555	0.00098	0.00068
Response options^2×					
Asymmetric	-0.04690	-0.00122	0.00031	-0.00005	-0.00006
Loading magnitude	-2.12451	-0.14685	0.02682	-0.00451	-0.00166
Loading magnitude^2	1.79085	0.12730	-0.01863	0.00381	0.00151
Sample size	-0.40475	0.01424	0.00006	0.00030	-0.00097
Sample size^2	0.17973	-0.00524	0.00020	-0.00011	0.00034
Number of factors	-0.10687	-0.00463	-0.00039	-0.00010	-0.00005
Asymmetric×					
Loading magnitude	3.71952	0.27558	0.11280	0.01327	0.00844
Loading magnitude^2	-1.17710	-0.18396	-0.07174	-0.00937	-0.00713
Sample size	0.29781	-0.00253	0.02437	-0.00219	-0.00393
Sample size^2	-0.16484	-0.00346	-0.00870	0.00072	0.00138
Number of factors	-0.81043	-0.03425	-0.00208	-0.00101	-0.00028
Loading magnitude×					
Sample size	16.43214	0.03858	-5.87140	0.01187	-0.04098
Sample size^2	-8.22119	-0.08583	2.14448	-0.00411	0.01586
Number of factors	1.82103	0.21559	0.65988	0.02703	-0.01793
Loading magnitude^2×					
Sample size	-15.03742	-0.14310	3.87122	0.00022	0.06458
Sample size^2	7.54665	0.12608	-1.41187	0.00015	-0.02336
Number of factors	5.02726	0.03351	-0.43878	-0.01413	0.04983
Sample size×					
Number of factors	0.39375	0.08076	0.09529	-0.00988	-0.02326
Sample size^2×					
Number of factors	-0.26943	-0.03848	-0.03378	0.00320	0.00784
Number of factors×					
Correlated factors	-2.51728	-0.05765	0.00487	-0.00223	-0.00481
R ²	.970	.810	.902	.903	.963
N	1,296	1,296	1,296	1,296	648

Note. MLR = MLR (Yuan & Bentler, 2000). The multiplication sign (×) indicates interaction

terms. For correct interpretation of the sample-size regression coefficient, divide the sample

1369 size by 1,000 before plugging it into the equation. Regression coefficients are unstandardized
1370 and uncentered. Independent variables with more than two simulated levels were entered
1371 additionally in quadratic form. SRMR is only available for comparing ML and DWLS
1372 because the SRMR point estimates are identical for models with ML and MLR estimators
1373 and models with DWLS and WLSMV estimators (Maydeu-Olivares et al., 2018). We
1374 omitted standard errors and p -values for clarity. Regression coefficients to derive tailored
1375 cutoffs for χ^2 are colored in gray. They heavily depend on the degrees of freedom and are,
1376 thus, barely useful for empirical models different from the ones in the paper.

Figures

Figure 1
Exemplary Population and Analysis Models for the Factor-Dimensionality Scenarios

Note. We chose to illustrate a model with six indicators for exemplary purposes here.

1382 **Figure 2**
1383 *Exemplary Population and Analysis Models for the Cross-Loading Scenarios*

1384
1385 *Note.* We chose to illustrate a model with six indicators, correlated factors, and two cross-
1386 loadings (i.e., cross-loadings exist for 33% of all six indicators) for exemplary purposes here.

Figure 3
Distribution of GOFs for Scenarios with Correctly Specified and Misspecified Factor Dimensionality Through the Manipulation of the Factor Correlation

Note. We displayed each GOF in its original metric and direction. We restricted the X-axis to increase the readability.

Figure 4
Distribution of GOFs for Scenarios with Correctly Specified and Misspecified Models Regarding Cross-Loadings

Note. The levels of the Y-axis refer to the magnitude of misspecification and proportion of misspecification, separated by a slash. We displayed each GOF in its original metric and direction. We split the figure by factor correlation and restricted the X-axis to increase the readability.

1401 **Figure 5**
1402 *Zero-Order Correlation Between Characteristics and GOFs of Correctly Specified One-*
1403 *Factor Models*

1404
1405 *Note.* We recoded GOFs so that lower values represented worse fit (i.e., χ^2 , χ^2/df , RMSEA,
1406 and SRMR were multiplied by -1). We only displayed SRMR for comparing ML and DWLS
1407 because the SRMR point estimates are identical for models estimated with ML or MLR and
1408 models estimated with DWLS or WLSMV (Maydeu-Olivares et al., 2018).

1409 **Figure 6**
1410 *Zero-Order Correlation Between Characteristics and GOFs of Correctly Specified Two-*
1411 *Factor Models*

1412
1413 *Note.* We recoded GOFs so that lower values represented worse fit (i.e., χ^2 , χ^2/df , RMSEA,
1414 and SRMR were multiplied by -1). We only displayed SRMR for comparing ML and DWLS
1415 because the SRMR point estimates are identical for models estimated with ML or MLR and
1416 models estimated with DWLS or WLSMV (Maydeu-Olivares et al., 2018).

Figure 7
Zero-Order Correlation Between Characteristics and GOFs of Models with Misspecified Factor Dimensionality

Note. We recoded GOFs so that lower values represented worse fit (i.e., χ^2 , χ^2/df , RMSEA, and SRMR were multiplied by -1). We only displayed SRMR for comparing ML and DWLS because the SRMR point estimates are identical for models estimated with ML or MLR and models estimated with DWLS or WLSMV (Maydeu-Olivares et al., 2018).

1425 **Figure 8**
1426 *Zero-Order Correlation Between Characteristics and GOFs of Models with Unmodeled*
1427 *Cross-Loadings*

1428
1429 *Note.* We recoded GOFs so that lower values represented worse fit (i.e., χ^2 , χ^2/df , RMSEA,
1430 and SRMR were multiplied by -1). We only displayed SRMR for comparing ML and
1431 DWLS because the SRMR point estimates are identical for models estimated with ML or
1432 MLR and models estimated with DWLS or WLSMV (Maydeu-Olivares et al., 2018).

Figure 9
Median Values of GOFs Conditioned on the Type of Estimator and Misspecification for Scenarios with Misspecified Factor Dimensionality

Note. We displayed each GOF in its original metric and direction.

1438 **Figure 10**
1439 *Median Values of GOFs Conditioned on the Type of Estimator and Misspecification for*
1440 *Scenarios with Unmodeled Cross-Loadings*

1441
1442 *Note.* We displayed each GOF in its original metric and direction. We split the figure by
1443 factor correlation.

1444 **Figure 11**
1445 *Median Values of GOFs Conditioned on Loading Magnitude and Misspecification for*
1446 *Scenarios with Misspecified Factor Dimensionality*

1447
1448 *Note.* We displayed each GOF in its original metric and direction.

1449 **Figure 12**
1450 *Median Values of GOFs Conditioned on Loading Magnitude and Misspecification for*
1451 *Scenarios with Unmodeled Cross-Loadings*

1452
1453 *Note.* We displayed each GOF in its original metric and direction. We split the figure by
1454 factor correlation.