# A robust alternative estimator for small to moderate sample SEM: Biascorrected factor score path analysis 

Ben Kelcey<br>University of Cincinnati, USA

## HI G H LI G H T S

- Conventional SEM estimators perform poorly in small to moderate samples.
- Bias corrected estimators offer a simple and robust alternative.
- We outline the method with an applied example and $R$ code.
- Results demonstrate the proposed estimator is largely unbiased and more efficient.


#### Abstract

Structural equation modeling with full information maximum likelihood estimation is the predominant method to empirically assess complex theories involving multiple latent variables in addiction research. Although full information estimators have many desirable properties including consistency, a major limitation in structural equation models is that they often sustain significant bias when implemented in small to moderate size studies (e.g., fewer than 100 or 200 ). Recent literature has developed a limited information estimator designed to address this limitation-conceptually implemented through a bias-corrected factor score path analysis approach-that has been shown to produce unbiased and efficient estimates in small to moderate sample settings. Despite its theoretical and empirical merits, literature has suggested that the method is underused because of three primary reasons-the methods are unfamiliar to applied researchers, there is a lack of practical and accessible guidance and software available for applied researchers, and comparisons against full information methods that are grounded in disciplinespecific examples are lacking. In this study, I delineate this method through a step-by-step analysis of a sequential mediation case study involving internet addiction. I provide example $R$ code using the lavaan package and data based on a hypothetical study of addiction. I examine the differences between the full and limited information estimators within the example data and subsequently probe the extent to which these differences are indicative of a consistent divergence between the estimators using a simulation study. The results suggest that the limited information estimator outperforms the conventional full information maximum likelihood estimator in small to moderate sample sizes in terms of bias, efficiency, and power.


## 1. Introduction

The use of latent variables to operationalize substantive theories of behavior traverses most areas of addiction research. One of the most common methods to empirically assess the relationships of latent variables is structural equation modeling. Structural equation models (SEMs) assess underlying theories by estimating measurement models that track differences among individuals on the latent variables using observable indicators and then connect these latent variables through structural models to quantify their relationships.

Conventionally, the measurement and structural parameters in a SEM have been estimated concurrently using full information maximum likelihood. Theoretical research has demonstrated that full information estimation of measurement and structural parameters produces unbiased parameter estimates in large samples (e.g., Gagne \& Hancock, 2006; Kmenta, 1971). However, this research has also shown that the finite-
sample bias associated with full information estimators-e.g., bias for both the structural path coefficients and their standard errors-can be sensitive to the balance between model complexity and sample size because the core properties of full information estimators (e.g., consistency) lean heavily on large sample or asymptotic theory that may not even approximately apply in finite samples (e.g., Gagne \& Hancock, 2006; Li \& Beretvas, 2013). For instance, within the context of SEM, samples of 100 to 200 are often considered a minimum in order to produce stable unbiased estimates while samples of less than 100 cases are often classified as untenable (e.g., Kline, 2011). More carefully, sample size recommendations in past research have often indicated that at least 10 to 20 cases per parameter will be needed to provide a minimal basis for unbiased estimation and inference (e.g., Wolf, Harrington, Clark, \& Miller, 2013). However, even these minimal requirements can be contingent upon, for example, the presence of moderate to high magnitudes of factor loadings and latent variable associations (e.g., Wolf et al., 2013).

[^0]Yet, many studies in addiction research draw on sophisticated theories involving multiple latent variables with samples of less than 100 (e.g., Bledsoe, 2006; Mirhashem et al., 2017), samples between 100 and 200 (e.g., Kelly, Masterman, \& Young, 2011; Miranda, TreloarPadovano, Gray, Wemm, \& Blanchard, in press; Spada, Nikcevic, Moneta, \& Wells, 2007), or models whose complexity outpaces the 10 to 20 cases per parameter minimum (e.g., Coriale et al., 2012). This limitation is not unique to the field of addiction research-past surveys that traverse disciplines have also widely reported the regular use of SEM in small to moderate samples (e.g., MacCallum \& Austin, 2000).

In this study, I introduce a little-known robust alternative for estimating SEMs-bias-corrected factor score path analysis (BCFSPA). BCFSPA is a limited information maximum likelihood estimator that addresses several key limitations of full information methods in SEMs while improving upon conventional limited information methods. Recent research has shown that BCFSPA methods tend to perform well-both in an absolute sense and relative to full information meth-ods-in a variety of highly practical and relevant settings including small to moderate sample sizes, multilevel settings, and with nonnormal variables (e.g., Devlieger \& Rosseel, 2017; Devlieger, Mayer, \& Rosseel, 2016; Kelcey, Cox, \& Dong, n.d.).

Below, I provide an accessible illustration of the method through an example that maps the potential processes and predecessors of internet addiction using sequential mediation. I first provide a brief conceptual outline of the BCFSPA method and follow with an illustrative analysis (with data and in $R$ in appendix). I then conduct a simulation study to probe its performance in data with non-normal error distributions and illuminate the differences between the BCFSPA method and the conventional full information method in terms of coefficient bias, efficiency, standard error bias, and statistical power. I finish with a discussion.

## 2. Bias-corrected factor score path analysis

### 2.1. Factor score path analysis

I begin with an outline of a historical alternative to full information parameter estimation in SEMs—factor score path analysis (FSPA; e.g., Lu, Kwan, Thomas, \& Cedzynski, 2011). The FSPA approach breaks down the system of equations operationalizing a theory using two primary steps: (a) estimate separate measurement models for each latent variable and (b) estimate a path analysis using the factor scores predicted by the resulting measurement models.

Prior research has shown that FSPA is often a practical and valuable approach for two primary reasons. First, the piecewise estimation of the components of the SEM reduces the model complexity for each stage, thus improving estimation stability and solution admissibility. These benefits are particularly pronounced in analyses of small to moderate samples and in analyses considering complex models because full information estimation of SEM parameters can often lead to improper solutions or a failure to converge (e.g., Gagne \& Hancock, 2006). A second commonly cited benefit is that piecewise estimation can constrain the effects of model misspecification such that its influence does not bias unrelated structural or measurement components (e.g., Bollen, 1996; Devlieger \& Rosseel, 2017). Full information estimation of parameters in SEMs typically does not yield this prop-erty-model misspecification in any part of the SEM can propagate substantial bias to other unrelated parts of the model.

Despite these benefits and the conceptual simplicity of FSPA, a wellknown and significant drawback to the method is that the parameter estimates are biased because the method does not fully incorporate the uncertainty and indeterminancy inherent in factor scores (e.g., Skrondal \& Laake, 2001). More specifically, in order to connect latent variables across measurement models, FSPA methods first directly predict the unobserved values of the latent variables and treat them as known in the subsequent path analyses. However, factor scores are not uniquely determined by the measurement models and thus a critical limitation of any factor scoring method is that it ignores this essential uncertainty. The implication of this
limitation in practice is that the method produces structural path coefficient estimates that are biased proportional to the degrees of indeterminancy present in the latent variables.

### 2.2. Bias-corrected factor score path analysis

Recent theoretical developments in estimation have, however, shown that the nature of the bias arising in the structural path coefficients in FSPA can be tracked as a function of the measurement model parameters (Croon, 2002). Recent literature has derived bias-corrected limited information estimators that refine the FSPA approach so that it yields unbiased estimates of structural path coefficient estimates (Devlieger \& Rosseel, 2017; Kelcey et al., 2018). Several studies have provided initial evidence of the promise of BCFSPA and have identified it as a robust alternative to full information estimation in SEMs. For instance, research has compared the robustness and performance of BCFSPA relative to full information methods in small sample sizes and with moderate model complexity (Lu et al., 2011), with non-normal indicators in simple regression (Devlieger et al., 2016), with measurement model misspecifications (Devlieger \& Rosseel, 2017), and with multilevel or clustered settings (Kelcey et al., 2018).

Despite the demonstrated potential of this method, few empirical studies in addiction research have employed the method. More broadly, recent reviews have suggested that the underuse of the method may be due to three reasons-the methods are unfamiliar to applied researchers, there is a lack of practical and accessible guidance and software available for applied researchers, and comparisons against full information methods that are grounded in discipline-specific examples are lacking (Lu et al., 2011). I address these limitations by providing an example analysis grounded in addiction research along with code implementing the analysis. I also contribute to the research base of the BCFSPA method by assessing the estimator against a full information estimator within a case study of sequential mediation using small to moderate samples and multiple non-normal error distributions.

## 3. Illustration

I outline the BCFSPA estimator by developing a hypothetical example regarding internet addiction. Our implementation focuses on one common type of structural equation model-sequential mediation-to examine the extent to which social support influences internet usage and addiction through emotion dysregulation (e.g., Mo, Chan, Chan, \& Lau, 2018). A conceptual diagram of the theory and the corresponding SEM is presented in Fig. 1.

Our illustrative example draws on three latent variables: social support (S), emotion dysregulation (D), internet addiction (A); each latent variable is represented as a circle in Fig. 1. In addition, I consider one observed var-iable-internet usage (U)—that is standardized to have a variance of one and is represented as a square in Fig. 1. In our particular application, I focus on the sequential mediation pathway that details the extent to which the influence of social support on internet addiction operates through emotion dysregulation and then internet usage. Statistically, I summarize this sequential mediation process as the product of relationships between social support and emotion dysregulation (path labeled $a$ in Fig. 1), emotion dysregulation and internet usage (path labeled $e$ in Fig. 1), and internet usage and internet addiction (path labeled $f$ in Fig. 1).

For the purposes of our illustration, I simulated data based on a sample of 100 cases (I explore a broader range of sample sizes in the next section; see Appendix for data generation and code). In this illustration I consider normally distributed error terms for each of the indicators. However, because addiction research often calls on variables with non-normal distributions that are not directly reproduced by correlation matrices, our subsequent Monte Carlo simulation comparing the limited and full information estimators purposefully considers several different types of non-normal error distributions and the robustness of the estimators to these types of violations.


Fig. 1. Conceptual diagram of example structural equation model for sequential mediation (quantified by aef) with path labels.
Note. $S$ refers to social support (with $S_{1}, S_{2}$ and $S_{3}$ as indicators), $D$ refers to emotion dysregulation (with $D_{1}, D_{2}, D_{3}, D_{4}$, and $D_{5}$ as indicators), A refers to internet addiction (with $\mathrm{A}_{1}, \mathrm{~A}_{2}, \mathrm{~A}_{3}$ and $\mathrm{A}_{4}$ as indicators), and U refers to internet usage.
Note. a refers to the Support-Emotion path; b refers to the Support-Addiction path; c refers to the Support-Usage path; d refers to the Emotion-Addiction path; e refers to the Emotion-Usage path; and f refers to the Usage-Addiction path.

### 3.1. Implementation

The BCFSPA estimator parallels the conventional FSPA estimator but differs in one key way-the conventional FSPA estimator uses the factor score variance-covariance matrix to estimate structural relationships whereas the bias-corrected approach introduces measurement model-based adjustments to correct the factor score variancecovariance matrix and thereby provide an unbiased estimate of the true variance-covariance matrix. Below I conceptually outline an implementation of the method and provide step-by-step $R$ code in the supplemental material using the lavaan package (Rosseel, 2012).

### 3.1.1. Step a

To implement the BCFSPA estimator, I first separately estimate confirmatory factor models for each latent variable (see example code in supplemental material). In our illustration, I estimate individual factor models for each of three latent factors: (a) social support using three indicators, (b) emotion dysregulation using five indicators, and (c) internet addiction using four indicators (see Fig. 1). Having fit the models, we can assess the adequacy of each one using the typical model fit indices (e.g., chi-square test of model fit). The resulting factor loadings for the example data for each factor under the BCFSPA and full
information estimators are presented in Table 1.

### 3.1.2. Step b

We must now forge structural connections among the variables to estimate path coefficients. With the BCFSPA estimator, we first predict factor scores for each latent variable using, for example, the regression method. Subsequently, we estimate the variance-covariance matrix of the factor scores along with any observed variables (e.g., internet usage). That is, although we conceptually predict factor scores, we do not use them at the individual-level but rather employ them in a limited fashion only to obtain an initial estimate of the variance-covariance matrix. The covariance matrix $(\Sigma)$ of factor scores for the example dataset is
$\Sigma=\left(\begin{array}{cccc}\mathrm{U} & \mathrm{A} & \mathrm{S} & \mathrm{D} \\ 1 & & & \\ .38 & .89 & & \\ -.03 & -.20 & .85 & \\ .15 & .42 & -.28 & .9\end{array}\right)$

### 3.1.3. Step $c$

Next, we correct the covariance matrix to obtain an estimate of the true covariances. I consider standardized solutions with the scale of each latent variable identified by setting the variance of that variable to unity in the measurement model. Alternative approaches such as fixing the loading of the first indicator to one can also be used (e.g., Devlieger et al., 2016). To implement these corrections with regression-based factor scores, we divide the covariance between each set of scores (as outlined in Eq. (1)) by the respective products of the factor score and loading matrices (see worked example for the covariance between social support and emotion dysregulation below and in appendix code).

Conceptually, these corrections parallel the classical test theory disattenuation corrections for a correlation between to unreliably measured constructs because the BCFSPA corrections principally leverage the unreliabilities of the latent variables to remove the attenuating effects of measurement error on the covariances of factor scores (Spearman, 1904). More specifically, the historical correction associated with classical test theory disattenuates an observed correlation by dividing it by the square root of the product of the latent variable reliabilities. This approach presumes a classical test theory measurement model (tau equivalence) is appropriate and assumes large sample or known reliabilities for the factors. In SEM, however, more complex measurement models are accommodated, the reliabilities of factors are unknown, and the associated indicator properties (e.g.,

Table 1
Measurement and structural model results for illustrative analysis.

|  | Parameter | Indicator | Emotion dysregulation (D) |  | Internet addiction (A) |  | Social support (S) |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  |  |  | SEM | BCFSPA | SEM | BCFSPA | SEM | BCFSPA |
| Measurement model | Factor loadings | 1 | 0.69 | 0.75 | 0.61 | 0.78 | 0.82 | 0.87 |
|  |  | 2 | 0.76 | 0.81 | 0.66 | 0.85 | 0.88 | 0.84 |
|  |  | 3 | 0.74 | 0.81 | 0.57 | 0.74 | 0.42 | 0.42 |
|  |  | 4 | 0.79 | 0.84 | 0.65 | 0.85 | - | - |
|  |  | 5 | 0.64 | 0.69 | - | - |  | - |
|  | Parameter (true) | SEM |  |  | BCFSPA |  |  |  |
|  |  | Estimate | SE(M) | SE(B) | Estimate | SE(B) |  |  |
| Structural model | a $(=-0.30)$ | $-0.40$ | 0.13 | 0.16 | $-0.37$ | $0.12$ |  |  |
|  | $\mathrm{b}(=-0.10)$ | $-0.14$ | 0.13 | 0.16 | $-0.10$ | 0.11 |  |  |
|  | $\mathrm{c}(=-0.04)$ | 0.05 | 0.12 | 0.12 | $0.03$ | $0.11$ |  |  |
|  | $\mathrm{d}(=0.40)$ | 0.51 | 0.14 | 0.18 | $0.43$ | 0.12 |  |  |
|  | $\mathrm{e}(=0.15)$ | 0.17 | 0.11 | 0.11 | 0.17 | 0.12 |  |  |
|  | $\mathrm{f}(=0.33)$ | 0.46 | 0.12 | 0.16 | 0.35 | 0.11 |  |  |
| Mediation effect | aef $(=-0.01)$ | $-0.03$ | - | 0.03 | -0.02 | 0.02 |  |  |

Note. SE(M) is model-based standard errors and SE(B) is bootstrapped standard errors. SEM is full information estimation. BCFSPA is the limited information bias corrected factor score path analysis.
factor loadings, error variance) are unknown and estimated from the data. These critical differences impede the use of the classical test theory disattenuation adjustment in SEM. The BCFSPA approach bridges this gap by mapping out the working relationship between factor covariances and factor score covariances and developing corrections on the basis of these relationships.

As an example, let us consider how to obtain an unbiased estimate of the true covariance between the latent constructs of social support $\left(\eta_{S}\right)$ and emotion dysregulation ( $\eta_{D}$ ). Croon (2002) showed that having estimated the measurement models, a corrected covariance can be obtained by dividing the covariance between the factor scores of social support ( $f_{S}$ ) and emotion dysregulation $\left(f_{D}\right)$ by the products of their factor score ( $\mathrm{A}_{\mathrm{S}}$ and $\mathrm{A}_{\mathrm{D}}$ ) and loading matrices $\left(\Lambda_{S}\right.$ and $\left.\Lambda_{D}\right)$
$\operatorname{cov}\left(\eta_{S}, \eta_{D}\right)=\frac{\operatorname{cov}\left(f_{S}, f_{D}\right)}{\mathbf{A}_{S} \boldsymbol{\Lambda}_{S} \boldsymbol{\Lambda}_{D}^{\prime} \mathbf{A}_{D}^{\prime}}$
The key insight conceptually linking the classical test theory disattenuation correction and the Croon (2002) correction is to recognize that matrix multiplications in the denominator of Eq. (2) produce the product of the construct reliabilities. That is, each matrix multiplication of the individual factor score and loading matrices (e.g., $\mathbf{A}_{S} \boldsymbol{\Lambda}_{S}$ ) produces an empirical estimate of its construct reliability on the basis of the measurement model properties. The net result is that a disattenuated estimate of the true covariance between, for example, social support and emotion dysregulation $\left(\operatorname{cov}\left(\eta_{S}, \eta_{D}\right)\right)$ can be obtained by dividing their observed factor score covariance by the product of the empirical reliability of the social support $\left(\mathbf{A}_{S} \boldsymbol{\Lambda}_{S}\right)$ and the empirical reliability of emotion dysregulation ( $\boldsymbol{\Lambda}_{D}{ }^{\prime} \mathbf{A}_{D}{ }^{\prime}$ ).

Next we correct the variances of the latent variables. To correct these variances, we simply set each term corresponding to a latent variable on the diagonal of the covariance matrix to one. The resulting corrected covariance matrix ( $\widetilde{\Sigma}$ ) becomes
$\widetilde{\Sigma}=\left(\begin{array}{cccc}\mathrm{U} & \mathrm{A} & \mathrm{S} & \mathrm{D} \\ .42 & 1 & & \\ -.04 & -.27 & 1 & \\ .16 & .52 & -.37 & 1\end{array}\right)$

### 3.1.4. Step d

Having obtained an unbiased estimate of the true covariance matrix, we now draw on a typical path analysis to obtain unbiased estimates of the true structural path coefficients. Specifically, we conduct a path analysis with the corrected covariance matrix as the sample covariance matrix input and sample size equal to the number of cases on our dataset (see supplemental material for example code).

### 3.1.5. Uncertainty

Once we have obtained BCFSPA estimates of the path coefficients, we can estimate the sampling variability of those estimates using, for example, a non-parametric bootstrap estimator. We estimate the sampling distribution of each path coefficient by sampling cases with replacement to create bootstrap replicates. With a sufficient number of replications, we can then estimate, for example, the standard errors as the standard deviation of the bootstrapped estimates for each path or confidence intervals based on percentiles of the bootstrapped estimates. For illustration, I use a sample of 500 bootstrap replications but larger samples of 1000 or 5000 are common. I implement a similar bootstrap approach for the full information estimator and also the conventional model-based standard errors based on large-sample theory.

### 3.1.6. Results

The resulting full information estimates and the BCFSPA estimates are presented in Table 1. Comparisons of the estimates for each path coefficient suggested two core differences. The first difference has been demonstrated in other studies but with different models and under different settings-the

BCFSPA coefficient estimates were nearly unbiased in each instance and uniformly demonstrated less bias than their full information counterparts. For the focal sequential mediation process, the BCFSPA estimates for the sequential mediation effect and each principal path (i.e., $a$, $e$, and $f$ ) were closer to the true parameter value than its full information counterpart (Table 1). The second difference was that the BCFSPA estimates tended to have less sampling variability-the standard errors of the BCFSPA (and confidence intervals) are smaller than their full information counterparts (see standard errors in Table 1).

Although this example was purposefully chosen to illustrate the expected differences between the estimators, the discrepancies in terms of bias align well with past research. Furthermore, the discrepancies in terms of uncertainty suggest that the BCFSPA estimator is more efficient-a result that has not been well-documented and completely investigated. In the next section, I probe the extent to which the observed disparities in both bias and sampling variability owe to consistent differences between the estimators in the context of our sequential mediation example.

## 4. Simulation

To further delineate the differences and provide a more formal comparison between the methods in terms of their expected performance, I conducted a Monte Carlo simulation study using the parameters values from the empirical example. Within the context of our sequential mediation example, our comparisons varied the sample size, factor loadings, error distribution, and the magnitude of the error variance. I considered sample sizes of $50,100,200$, and 300 and factor loadings ranging from 0.4 to 0.85 . In terms of errors, I considered the following distributions: chi-squared, normal, $t$, log-uniform, and exponential-normal. For the magnitudes of the error variances, I considered high and low coefficient of determination conditions for each of the distributions and sample sizes. I evaluated the absolute and relative performances of these methods using four criteria: path coefficient relative bias, standard error relative bias, magnitude of standard errors, and power.

### 4.1. Results

### 4.1.1. Bias in coefficients

The results of our simulation in terms of the relative bias of path coefficients are outlined in Fig. 2 by path coefficient, sample size, and method. The results strongly suggested that the BCFSPA estimator consistently returns estimates that incur minimal to no bias even in samples as small as 50 or 100. In contrast, the full information estimator demonstrated significant bias for most path coefficients with samples less than about 200. Collectively, the results strongly suggested that the differences in path coefficient estimates we observed in our illustration (i.e., in Table 1) are indicative of true differences between the estimators.

### 4.1.2. Standard errors

I next compared the extent to which model-based and bootstrapped standard errors accurately tracked the variability of point estimates across samples as well as the relative magnitude of the sampling variability of the two estimators. In addition to the bootstrap, our analyses considered conventional model-based estimates of standard errors for the full information method. These model-based standard errors draw on the asymptotic normality of the path coefficient estimates and are the standard errors reported by default in most software (e.g., Rosseel, 2012). Fig. 3 reports the relative bias of the standard errors, Fig. 4 provides an example of the distributions of the coefficient estimates by estimator and path, and Fig. 5 compares the magnitudes of the true variability across samples.

With regard to the bias of the estimated standard errors, our analyses returned two primary results (Fig. 3). First, the non-parametric bootstrap approach was able to very accurately track the standard errors, even in samples of 50 . In contrast, full information estimator, the bootstrap approach typically returned highly biased estimates of the sampling variability for most paths. The conventional model-based


Fig. 2. Average relative bias of coefficients across error distributions by path, sample size, and method (lower case is BCFSPA, uppercase is full information parameter estimation).
Note. A and a refer to the Support-Emotion path; B and b refer to the Support-Addiction path; C and c refer to the Support-Usage path; D and d refer to the EmotionAddiction path; E and e refer to the Emotion-Usage path; and F and frefer to the Usage-Addiction path; See Fig. 1 for more details.


Fig. 3. Average relative bias of standard errors across error distributions by path, sample size, and method (lower case is BCFSPA, uppercase is full information with bootstrap-based standard errors, and * is full information with model-based standard errors).
Note. A and a refer to the Support-Emotion path; B and b refer to the Support-Addiction path; C and c refer to the Support-Usage path; D and d refer to the EmotionAddiction path; E and e refer to the Emotion-Usage path; and F and frefer to the Usage-Addiction path; See Fig. 1 for more details.
standard errors tended to be more accurate for the full information estimator but even then their relative bias only approached zero in samples greater than 100 (Fig. 3).

To compare the magnitudes of the true sampling variability across estimators, I drew on the standard deviation of each path coefficient
across samples. In large samples, full information estimators are more efficient than their limited information counterparts. However, this need not be the case in finite samples. In this way, an important and open question with regard to the performance of the BCFSPA estimator is its efficiency relative to the full information estimator.


Fig. 4. Distribution of coefficient estimates by method and path (solid line: BCFSPA; dashed line: full information).
Note. A and a refer to the Support-Emotion path; B and b refer to the Support-Addiction path; C and c refer to the Support-Usage path; D and d refer to the EmotionAddiction path; E and e refer to the Emotion-Usage path; and F and frefer to the Usage-Addiction path; See Fig. 1 for more details.


Fig. 5. Average magnitude of sampling variability of estimators across path coefficients.
Note. A and a refer to the Support-Emotion path; B and b refer to the Support-Addiction path; C and c refer to the Support-Usage path; D and d refer to the EmotionAddiction path; E and e refer to the Emotion-Usage path; and F and frefer to the Usage-Addiction path; See Fig. 1 for more details.

The results of our study consistently reported that the BCFSPA estimator was much more efficient and maintained distributions that were much more concentrated around the true path coefficients than the full information estimator. As an example, Fig. 4 outlines the comparative distributions of the estimators by path for the first simulation condition. For each path, the empirical distribution of estimates was more dispersed under the full
information estimator than the BCFSPA estimator. Collectively, the results indicated that the BCFSPA estimator had lower sampling variability than the full information estimator when samples were less than about 200 and similar sampling variability with sample sizes of about 200 (Fig. 5).


Fig. 6. Average power across error distributions by path, sample size, and method (lower case is BCFSPA, uppercase is full information with model-based standard errors, and * is full information with bootstrap-based standard errors).
Note. A and a refer to the Support-Emotion path; B and b refer to the Support-Addiction path; C and c refer to the Support-Usage path; D and d refer to the EmotionAddiction path; E and e refer to the Emotion-Usage path; and F and frefer to the Usage-Addiction path; See Fig. 1 for more details.

### 4.1.3. Power

Last I examined the power with which each estimator could detect non-zero path coefficients using standard Wald tests for each parameter (Fig. 6). Comparisons of power between estimators are complicated by differences in bias across the methods-BCFSPA produced largely unbiased estimates whereas the full information estimator routinely demonstrated upward bias. The implication is that the tests of path coefficients under the full information estimator with model-based or bootstrap-based standard errors practically reduce to how well each can detect an incorrect and inflated effect-this critical limitation that obscures the basis for inference and comparison. Despite this critical limitation, our analyses compared the power of the BCFSPA estimator with bootstrapped standard errors to the full information estimator with model-based and bootstrap-based standard errors in order to benchmark the performance of the BCFSPA.

The results for power were more equivocal than those under the previous criteria and depend to some extent on whether the bootstrap- or model-based standard errors are used (see Fig. 6). For the downstream paths-paths $d, e$ and $f$-the BCFSPA estimator was more powerful across all sample sizes regardless of the method used to obtain full information standard errors. For the $a$ and $b$ paths, the estimators had similar power but the full information bootstrap-based approach tended to underperform. The results of the $c$ path briefly touch upon the type one error rate and suggested that all the approaches reasonably maintain the nominal error rate. Overall, the results suggested that on average the BCFSPA estimator offered a small to moderate advantage in terms of power over the full information estimator. Moreover, when viewed alongside the performances on the other criteria, the results strongly suggest the BCFSPA estimator would be preferred because it returns virtually unbiased estimates and can detect them with power that is similar to or greater than that of the full information estimator.

## 5. Discussion

Applied literature has recognized that the benefits of empirical studies of behavioral theories and processes are not limited to only large scale
studies-small to moderate scale studies can also offer critical contributions to theory and practice when they are well executed (e.g., Bodner \& Bliese, 2017; Walton, 2014). At the same time, many studies in addictive behavior that draw on small to moderate samples also draw on sophisticated theories that require SEMs. This combination-small to moderate sample sizes coupled with sophisticated SEMs-poses significant challenges for full information estimation methods because stable and unbiased estimates under this method demand a large sample-to-parameter ratio.

In this study, I outlined an attractive alternative approach and estimator-BCFSPA. The results of our study coupled with those of other studies suggested that with samples of about 200 to 300 or less (depending on model complexity and factor indeterminacies), the limited information BCFSPA estimator is likely to outperform the conventional full information estimator in terms of bias, error variance, and power. The results also suggested the efficacy of the BCFSPA estimator may not be sensitive to the types of non-normal indicator error distributions addiction researchers often face when tracking latent variables.

Although the BCFSPA estimator performed very well in the current and in past studies, it also has some current limitations. First, estimation of individual factor models requires at least three indicators per construct or with fewer indicators additional factor loading constraints (i.e., equal loadings). Second, implementation of the method becomes more complicated when there is within indicator multidimensionality (e.g., cross loadings) because rather than estimate individual factor models we must estimate factor models that correctly and judiciously apportion the system in ways that are faithful to the original SEM but also favorable for estimation. Third, BCFSPA currently lacks model fit statistics. For instance, a common diagnostic tool for assessing the fit of a SEM under full information estimation is the chi-square test of model fit. Although such tests are available for the individual factor models, such global tests for the overall SEM are not currently available.

In conclusion, the results suggest that BCFSPA addresses the sample size limitation associated with full information estimation for many types of SEMs. A major obstacle to implementing the BCFSPA estimator has been its accessibility and its practical implementation in software. In an effort to facilitate and encourage the consideration and use of this
approach, I have included example $R$ syntax in the appendix.

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## Contributors

Author A is the sole author of the manuscript.

## Conflict of interest

Author A declares no conflict of interest.

## Appendix A. Results of simulation

Table A1
Relative bias of path coefficients.


Note. BC indicates BCFSPA and Full indicates full information.
Note. $\chi_{1}{ }^{2}$ refers to the chi-squared distribution with one degree of freedom, $\mathrm{N}(0,1)$ refers to the standard normal distribution, $\mathrm{t}(3)$ refers to the t -distribution with 3 degrees of freedom, $\ln (u n i f(1100))$ refers to a log-uniform distribution with bounds of 1 and 100 , and $\operatorname{Exp}(n o r m a l(0,1)$ refers to the exponential of the standard normal distribution.

Table A2

Empirical standard deviation of path coefficient estimates.

| Condition | Error distribution | a |  | b |  | c |  | d |  | e |  | f |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  |  | BC | Full | BC | Full | BC | Full | BC | Full | BC | Full | BC | Full |
| $\mathrm{n}=50$ | $\chi_{1}{ }^{2}$ | 0.16 | 0.34 | 0.15 | 15.05 | 0.15 | 0.30 | 0.16 | 4.43 | 0.15 | 0.16 | 0.15 | 4.94 |
|  | $\chi_{1}{ }^{2} / 2$ | 0.14 | 0.16 | 0.14 | 0.18 | 0.15 | 0.16 | 0.13 | 0.18 | 0.15 | 0.14 | 0.13 | 0.17 |
|  | $\mathrm{N}(0,3)$ | 0.19 | 0.52 | 0.20 | 63.52 | 0.16 | 0.22 | 0.19 | 24.96 | 0.17 | 0.18 | 0.16 | 25.91 |
|  | $\mathrm{N}(0,1)$ | 0.15 | 0.19 | 0.16 | 0.22 | 0.15 | 0.16 | 0.15 | 0.20 | 0.15 | 0.15 | 0.14 | 0.19 |
|  | t(3) | 0.18 | 1.51 | 0.17 | 19.21 | 0.15 | 25.05 | 0.18 | 7.19 | 0.17 | 0.74 | 0.15 | 9.14 |
|  | t(3)/2 | 0.15 | 0.17 | 0.14 | 0.18 | 0.15 | 0.16 | 0.14 | 0.19 | 0.14 | 0.14 | 0.14 | 0.18 |
|  | $\ln ($ unif(1100)) | 0.15 | 0.18 | 0.14 | 0.19 | 0.14 | 0.15 | 0.14 | 0.19 | 0.15 | 0.15 | 0.14 | 0.18 |
|  | $2 \ln ($ unif( 1100 ) ) | 0.18 | 0.47 | 0.17 | 55.75 | 0.16 | 0.36 | 0.18 | 24.37 | 0.17 | 0.19 | 0.16 | 32.02 |
|  | $\operatorname{Exp}($ norm(0,1)) | 0.18 | 1.95 | 0.19 | 120.31 | 0.16 | 40.83 | 0.19 | 63.73 | 0.18 | 1.24 | 0.16 | 45.18 |
|  | $\operatorname{Exp}\left(\operatorname{norm}\left(0,0.5^{-5}\right)\right)$ | 0.16 | 0.20 | 0.15 | 0.20 | 0.15 | 0.17 | 0.15 | 0.20 | 0.15 | 0.15 | 0.14 | 0.18 |
| Average$\mathrm{n}=100$ |  | 0.16 | 0.57 | 0.16 | 27.48 | 0.15 | 6.76 | 0.16 | 12.56 | 0.16 | 0.32 | 0.15 | 11.81 |
|  | $\chi_{1}{ }^{2}$ | 0.12 | 0.15 | 0.12 | 0.16 | 0.11 | 0.12 | 0.11 | 0.15 | 0.11 | 0.11 | 0.10 | 0.13 |
|  | $\chi_{1}{ }^{2} / 2$ | 0.10 | 0.11 | 0.10 | 0.12 | 0.10 | 0.11 | 0.10 | 0.12 | 0.10 | 0.10 | 0.09 | 0.11 |
|  | $\mathrm{N}(0,3)$ | 0.15 | 0.20 | 0.12 | 20.84 | 0.12 | 0.15 | 0.13 | 3.96 | 0.13 | 0.13 | 0.11 | 8.09 |
|  | $\mathrm{N}(0,1)$ | 0.11 | 0.12 | 0.11 | 0.13 | 0.11 | 0.12 | 0.10 | 0.13 | 0.11 | 0.10 | 0.10 | 0.12 |
|  | t(3) | 0.14 | 0.17 | 0.13 | 0.19 | 0.11 | 0.13 | 0.12 | 0.18 | 0.12 | 0.12 | 0.10 | 0.13 |
|  | $\mathrm{t}(3) / 2$ | 0.10 | 0.12 | 0.11 | 0.13 | 0.11 | 0.11 | 0.10 | 0.12 | 0.11 | 0.10 | 0.10 | 0.12 |
|  | $\ln ($ unif(1100)) | 0.11 | 0.12 | 0.11 | 0.13 | 0.11 | 0.11 | 0.10 | 0.12 | 0.11 | 0.10 | 0.09 | 0.12 |
|  | $2 \ln (u n i f(1100))$ | 0.14 | 0.18 | 0.13 | 19.56 | 0.11 | 0.13 | 0.13 | 3.46 | 0.12 | 0.12 | 0.11 | 1.25 |
|  | $\operatorname{Exp}$ (norm(0,1)) | 0.16 | 0.23 | 0.15 | 38.56 | 0.12 | 0.17 | 0.15 | 14.01 | 0.13 | 0.14 | 0.12 | 22.12 |
|  | $\operatorname{Exp}\left(\operatorname{norm}\left(0,0.5^{-5}\right)\right)$ | 0.11 | 0.13 | 0.11 | 0.13 | 0.11 | 0.11 | 0.10 | 0.13 | 0.11 | 0.11 | 0.09 | 0.12 |
| Average$\mathrm{n}=200$ |  | 0.12 | 0.15 | 0.12 | 8.00 | 0.11 | 0.13 | 0.11 | 2.24 | 0.12 | 0.11 | 0.10 | 3.23 |
|  | $\chi_{1}{ }^{2}$ | 0.10 | 0.11 | 0.09 | 0.11 | 0.08 | 0.09 | 0.08 | 0.11 | 0.08 | 0.08 | 0.07 | 0.09 |
|  | $\chi_{1}^{2} / 2$ | 0.07 | 0.08 | 0.07 | 0.08 | 0.08 | 0.08 | 0.07 | 0.08 | 0.07 | 0.07 | 0.06 | 0.08 |
|  | $\mathrm{N}(0,3)$ | 0.10 | 0.12 | 0.10 | 0.13 | 0.09 | 0.10 | 0.09 | 0.12 | 0.09 | 0.09 | 0.08 | 0.10 |
|  | $\mathrm{N}(0,1)$ | 0.08 | 0.09 | 0.08 | 0.09 | 0.08 | 0.08 | 0.07 | 0.09 | 0.07 | 0.07 | 0.07 | 0.08 |
|  | t(3) | 0.11 | 0.12 | 0.10 | 0.12 | 0.09 | 0.09 | 0.09 | 0.12 | 0.09 | 0.09 | 0.08 | 0.10 |
|  | $t(3) / 2$ | 0.08 | 0.08 | 0.07 | 0.09 | 0.08 | 0.08 | 0.07 | 0.09 | 0.08 | 0.07 | 0.06 | 0.08 |
|  | $\ln ($ unif(1100)) | 0.08 | 0.09 | 0.07 | 0.08 | 0.08 | 0.08 | 0.07 | 0.09 | 0.08 | 0.07 | 0.06 | 0.08 |
|  | $2 \ln ($ unif(1100)) | 0.11 | 0.12 | 0.10 | 0.13 | 0.09 | 0.10 | 0.09 | 0.12 | 0.08 | 0.08 | 0.08 | 0.10 |
|  | $\operatorname{Exp}($ norm $(0,1))$ | 0.13 | 0.16 | 0.10 | 0.15 | 0.09 | 0.10 | 0.10 | 0.14 | 0.09 | 0.09 | 0.08 | 0.10 |
|  | $\operatorname{Exp}\left(\right.$ norm $\left.\left(0,0.5^{.5}\right)\right)$ | 0.08 | 0.09 | 0.08 | 0.09 | 0.08 | 0.08 | 0.07 | 0.09 | 0.08 | 0.08 | 0.07 | 0.08 |
| Average$\mathrm{n}=300$ |  | 0.09 | 0.11 | 0.09 | 0.11 | 0.08 | 0.09 | 0.08 | 0.11 | 0.08 | 0.08 | 0.07 | 0.09 |
|  | $\chi_{1}{ }^{2}$ | 0.08 | 0.08 | 0.07 | 0.08 | 0.07 | 0.07 | 0.07 | 0.08 | 0.07 | 0.06 | 0.06 | 0.07 |
|  | $\chi_{1}{ }^{2} / 2$ | 0.06 | 0.07 | 0.06 | 0.07 | 0.06 | 0.06 | 0.06 | 0.07 | 0.06 | 0.06 | 0.05 | 0.07 |
|  | $\mathrm{N}(0,3)$ | 0.09 | 0.10 | 0.08 | 0.10 | 0.07 | 0.08 | 0.07 | 0.09 | 0.07 | 0.07 | 0.06 | 0.07 |
|  | $\mathrm{N}(0,1)$ | 0.07 | 0.07 | 0.06 | 0.07 | 0.06 | 0.06 | 0.06 | 0.07 | 0.06 | 0.06 | 0.05 | 0.07 |
|  | t(3) | 0.09 | 0.10 | 0.08 | 0.10 | 0.07 | 0.08 | 0.07 | 0.09 | 0.07 | 0.07 | 0.06 | 0.07 |
|  | t(3)/2 | 0.06 | 0.07 | 0.06 | 0.07 | 0.06 | 0.06 | 0.06 | 0.07 | 0.06 | 0.06 | 0.05 | 0.06 |
|  | $\ln ($ unif(1100)) | 0.06 | 0.07 | 0.06 | 0.07 | 0.06 | 0.07 | 0.06 | 0.07 | 0.06 | 0.06 | 0.06 | 0.07 |
|  | $2 \ln ($ unif( 1100 ) $)$ | 0.09 | 0.10 | 0.08 | 0.10 | 0.07 | 0.08 | 0.08 | 0.10 | 0.07 | 0.07 | 0.06 | 0.08 |
|  | $\operatorname{Exp}($ norm $(0,1))$ | 0.13 | 0.12 | 0.10 | 0.12 | 0.08 | 0.09 | 0.09 | 0.11 | 0.07 | 0.07 | 0.06 | 0.08 |
|  | $\operatorname{Exp}\left(\operatorname{norm}\left(0,0.5^{5}\right)\right)$ | 0.07 | 0.07 | 0.06 | 0.07 | 0.06 | 0.07 | 0.06 | 0.07 | 0.06 | 0.06 | 0.06 | 0.07 |
| Average |  | 0.08 | 0.09 | 0.07 | 0.09 | 0.07 | 0.07 | 0.07 | 0.08 | 0.07 | 0.06 | 0.06 | 0.07 |
| Overall average |  | 0.12 | 0.23 | 0.11 | 9.12 | 0.10 | 1.80 | 0.11 | 3.83 | 0.11 | 0.15 | 0.09 | 3.89 |

Note. $\chi_{1}{ }^{2}$ refers to the chi-squared distribution with one degree of freedom, $\mathrm{N}(0,1)$ refers to the standard normal distribution, $\mathrm{t}(3)$ refers to the t -distribution with 3 degrees of freedom, $\ln (\operatorname{unif}(1100))$ refers to a log-uniform distribution with bounds of 1 and 100 , and $\operatorname{Exp}($ normal $(0,1)$ refers to the exponential of the standard normal distribution.

Table A3
Relative bias of path coefficient standard errors.

| n | Error dist | a |  |  |  | b |  |  |  | c |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  |  | BC |  | Full |  | BC |  | Full |  | BC |  | Full |
|  |  | B | M | B | M | B | M | B | M | B | M | B |
| 50 | $\chi_{1}{ }^{2}$ | 0.01 | -0.15 | 18.93 | 3.12 | 0.04 | -0.18 | 4.43 | 3.85 | 0 | 0.08 | 18.59 |
|  | $\chi_{1}{ }^{2} / 2$ | -0.01 | -0.03 | 0.09 | -0.06 | -0.02 | -0.07 | 1.98 | -0.09 | -0.03 | 0.11 | 0.71 |
|  | $\mathrm{N}(0,3)$ | -0.06 | -0.28 | 66.89 | 1.99 | -0.01 | -0.34 | 3.79 | -0.9 | 0.03 | 0.01 | 186.42 |
|  | $\mathrm{N}(0,1)$ | 0 | -0.12 | 3.37 | -0.11 | -0.04 | -0.18 | 29.09 | -0.18 | -0.02 | 0.1 | 2.94 |
|  | t(3) | -0.05 | -0.24 | 4.89 | 5.6 | 0.07 | -0.24 | 11.09 | 0.39 | 0.02 | 0.06 | -0.23 |
|  | t (3)/2 | -0.02 | -0.08 | 0.09 | -0.08 | 0.01 | -0.08 | 9.24 | -0.1 | -0.03 | 0.11 | 0.66 |
|  | $\ln ($ unif (1100)) | -0.01 | -0.1 | 0.06 | -0.12 | 0.02 | -0.1 | 6.74 | -0.1 | 0.03 | 0.17 | 0.07 |
|  | $2 \ln ($ unif (1100)) | -0.04 | -0.26 | 36.47 | 0.21 | 0.12 | -0.24 | 4.82 | 6.83 | 0.05 | 0.04 | 61.82 |
|  | Exp(norm (0,1)) | -0.04 | -0.24 | 10.9 | 18.3 | 0.02 | -0.31 | 3.05 | 0.11 | 0.03 | 0.01 | -0.23 |
|  | $\begin{aligned} & \operatorname{Exp}(\text { norm } \\ & \left.\left(0,0.5^{5}\right)\right) \end{aligned}$ | -0.06 | -0.16 | 0.2 | -0.17 | -0.02 | -0.14 | 43.45 | -0.14 | -0.05 | 0.07 | 11.79 |
| Absolute average |  | 0.03 | 0.17 | 14.19 | 2.98 | 0.04 | 0.19 | 11.77 | 1.27 | 0.03 | 0.08 | 28.35 |
| 100 | $\chi_{1}{ }^{2}$ | 0.04 | -0.21 | 10.35 | -0.04 | 0.01 | -0.23 | 138.04 | -0.08 | 0.02 | 0.03 | 8.26 |


|  | $\chi_{1}{ }^{2} / 2$ |  | 0 | －0．06 | 0.03 | －0．03 | －0．01 | －0．09 | 0.03 |  | －0．06 | －0．01 | 0.1 | 0.01 |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | $\mathrm{N}(0,3)$ |  | －0．02 | －0．36 | 4.93 | －0．15 | 0.13 | －0．27 | 0.49 |  | －0．99 | 0.01 | －0．07 | 23.1 |
|  | $\mathrm{N}(0,1)$ |  | 0.04 | －0．11 | 0.09 | －0．04 | 0 | －0．15 | 0.07 |  | －0．07 | －0．02 | 0.04 | 0 |
|  | t（3） |  | －0．01 | －0．3 | 10.36 | －0．07 | 0.01 | －0．31 | 193.31 |  | －0．12 | 0.01 | －0．02 | 15.48 |
|  | t（3）／2 |  | 0.02 | －0．06 | 0.06 | －0．02 | －0．03 | －0．14 | 0.39 |  | －0．1 | －0．04 | 0.05 | －0．02 |
|  | $\ln ($ unif（1100）） |  | －0．02 | －0．12 | 0.03 | －0．07 | －0．02 | －0．14 | 0.04 |  | －0．09 | －0．03 | 0.04 | －0．01 |
|  | $2 \ln$（unif（1100）） |  | 0.06 | －0．3 | 1.55 | －0．08 | 0.08 | －0．31 | 1.09 |  | －0．99 | 0.08 | 0.01 | 30.96 |
|  | Exp（norm（0，1）） |  | －0．11 | －0．41 | 8.72 | －0．14 | 0 | －0．38 | 2.55 |  | －0．99 | 0.02 | －0．08 | 53.86 |
|  | $\begin{aligned} & \text { Exp(norm } \\ & \left.\left(0,0.5^{5}\right)\right) \end{aligned}$ |  | 0.01 | －0．12 | 0.11 | －0．05 | －0．02 | －0．16 | 2.15 |  | －0．08 | 0.01 | 0.08 | 0.73 |
| Abso | verage |  | 0.03 | 0.21 | 3.62 | 0.07 | 0.03 | 0.22 | 33.82 |  | 0.36 | 0.03 | 0.05 | 13.24 |
| 200 | $\chi_{1}{ }^{2}$ |  | －0．03 | －0．29 | 0.02 | －0．10 | 0.01 | －0．25 | 1.89 |  | －0．04 | －0．01 | －0．03 | 0.02 |
|  | $\chi_{1}{ }^{2} / 2$ |  | －0．02 | －0．07 | －0．01 | －0．03 | 0.00 | －0．08 | 0.02 |  | －0．02 | －0．03 | 0.05 | －0．02 |
|  | $\mathrm{N}(0,3)$ |  | 0.11 | －0．34 | 0.36 | －0．01 | －0．01 | －0．39 | 10.71 |  | －0．11 | －0．05 | －0．15 | 2.44 |
|  | $\mathrm{N}(0,1)$ |  | 0.03 | －0．12 | 0.05 | －0．01 | 0.00 | －0．16 | 0.03 |  | －0．04 | －0．01 | 0.02 | 0.02 |
|  | t（3） |  | 0.01 | －0．36 | 0.18 | －0．06 | 0.01 | －0．33 | 22.27 |  | －0．06 | 0.01 | －0．07 | 1.94 |
|  | t（3）／2 |  | －0．02 | －0．10 | 0.00 | －0．03 | －0．04 | －0．14 | －0．01 |  | －0．06 | －0．04 | 0.02 | －0．02 |
|  | $\ln ($ unif（1100）） |  | －0．03 | －0．13 | －0．01 | －0．05 | 0.02 | －0．10 | 0.06 |  | 0.00 | －0．02 | 0.04 | 0.00 |
|  | $2 \ln$（unif（1100）） |  | 0.08 | －0．35 | 0.28 | －0．05 | 0.01 | －0．38 | 14.88 |  | －0．08 | －0．01 | －0．12 | 1.94 |
|  | Exp（norm（0，1）） |  | －0．07 | －0．49 | 0.89 | －0．13 | 0.05 | －0．40 | 122.16 |  | －0．07 | 0.03 | －0．11 | 13.40 |
|  | Exp（norm $\left.\left(0,0.5^{.5}\right)\right)$ |  | 0.01 | －0．13 | 0.04 | －0．02 | －0．02 | －0．17 | 0.01 |  | －0．05 | －0．04 | －0．02 | －0．02 |
| Abso | average |  | 0.04 | 0.24 | 0.18 | 0.05 | 0.02 | 0.24 | 17.20 |  | 0.05 | 0.03 | 0.06 | 1.98 |
| 300 | $\chi_{1}{ }^{2}$ |  | 0.02 | －0．25 | 0.06 | －0．02 | 0.01 | －0．26 | 0.05 |  | －0．03 | －0．05 | －0．10 | －0．02 |
|  | $\chi_{1}{ }^{2} / 2$ |  | －0．02 | －0．08 | －0．01 | －0．03 | －0．01 | －0．08 | 0.00 |  | －0．02 | －0．03 | 0.04 | －0．02 |
|  | $\mathrm{N}(0,3)$ |  | 0.10 | －0．35 | 0.09 | －0．06 | 0.04 | －0．35 | 1.76 |  | －0．02 | －0．02 | －0．13 | 0.02 |
|  | $\mathrm{N}(0,1)$ |  | －0．01 | －0．15 | 0.01 | －0．03 | －0．02 | －0．18 | 0.00 |  | －0．05 | 0.04 | 0.06 | 0.06 |
|  | t（3） |  | 0.02 | －0．37 | 0.05 | －0．08 | －0．03 | －0．37 | 0.70 |  | －0．10 | －0．02 | －0．11 | 0.01 |
|  | ＊かっの |  | $\bigcirc \mathrm{nn}$ | $\bigcirc \mathrm{nn}$ | $\bigcirc 01$ | n ¢ | n n | ¢ 11 | n n |  | $\bigcirc \mathrm{n}$ | n 01 | n 01 | n n |
|  | In（unit（1100）） |  | －0．01 | －0．12 | 0.00 | －0．03 | 0.04 | －0．09 | 0.06 |  | 0.02 | －0．04 | 0.00 | －0．03 |
|  | $2 \ln$（unif（1100）） |  | 0.10 | －0．34 | 0.12 | －0．03 | 0.01 | －0．37 | 4.44 |  | －0．09 | 0.00 | －0．11 | 0.02 |
|  | Exp（norm（0，1）） |  | －0．15 | －0．57 | 0.47 | －0．07 | －0．05 | －0．48 | 45.94 |  | －0．07 | －0．05 | －0．22 | 5.41 |
|  | $\begin{aligned} & \operatorname{Exp}(\text { norm } \\ & \left.\left(0,0.5^{5}\right)\right) \end{aligned}$ |  | 0.00 | －0．15 | 0.01 | －0．02 | －0．02 | －0．17 | 0.00 |  | －0．04 | －0．01 | 0.01 | 0.01 |
| Absol | average |  | 0.04 | 0.25 | 0.08 | 0.04 | 0.02 | 0.25 | 5.30 |  | 0.05 | 0.03 | 0.08 | 0.56 |
| Over | solute average |  | 0.04 | 0.21 | 4.52 | 0.78 | 0.03 | 0.22 | 17.02 |  | 0.43 | 0.03 | 0.07 | 11.03 |
| n |  | c | d |  |  |  | e |  |  |  | f |  |  |  |
|  |  | Full | BC |  | Full |  | BC |  | Full |  | BC |  | Full |  |
|  |  | M | B | M | B | M | B | M | B | M | B | M | B | M |
| 50 |  | 7.14 | 0.04 | －0．18 | 8.8 | 1.1 | 0.01 | 0.05 | 0.89 | 0.9 | －0．01 | －0．09 | 5.5 | 1 |
|  |  | －0．08 | 0 | －0．01 | 0.71 | －0．08 | －0．01 | 0.12 | 0.01 | －0．01 | 0.02 | 0.05 | 1.49 | －0．07 |
|  |  | 0.72 | 0.07 | －0．3 | 6.12 | －0．96 | 0.06 | －0．02 | 3.72 | －0．02 | 0.07 | －0．14 | 4.97 | －0．98 |
|  |  | －0．09 | 0.02 | －0．08 | 12.94 | －0．09 | 0.01 | 0.09 | 0.07 | －0．02 | 0.02 | 0 | 11.24 | －0．11 |
|  |  | 6.02 | 0.05 | －0．24 | 16.23 | －0．35 | －0．02 | －0．04 | －0．18 | 3.29 | 0.1 | －0．05 | 12.63 | －0．47 |
|  |  | －0．07 | －0．02 | －0．05 | 3.32 | －0．09 | 0.02 | 0.13 | 0.06 | 0.01 | －0．02 | 0 | 3.39 | －0．1 |
|  |  | －0．02 | 0.02 | －0．06 | 2.85 | －0．05 | －0．01 | 0.07 | －0．02 | －0．04 | 0.02 | 0.03 | 2.86 | －0．08 |
|  |  | 1.02 | 0.13 | －0．25 | 7.83 | 2.32 | 0 | －0．07 | 2.9 | 0.13 | 0.08 | －0．12 | 6.74 | 1.21 |
|  |  | 7.27 | 0.05 | －0．27 | 3.62 | 0.19 | －0．05 | －0．09 | －0．25 | 5.34 | 0.11 | －0．09 | 5.51 | 1.03 |
|  |  | －0．1 | 0.01 | －0．08 | 12.9 | －0．1 | 0.01 | 0.09 | 0.21 | －0．01 | 0.03 | 0.03 | 17.78 | －0．08 |
| Absol | average | 2.25 | 0.04 | 0.15 | 7.53 | 0.53 | 0.02 | 0.08 | 0.83 | 0.98 | 0.05 | 0.06 | 7.21 | 0.51 |
| 100 |  | －0．04 | 0.04 | －0．15 | 47.8 | －0．03 | 0.05 | 0.06 | 0.36 | 0.03 | 0.01 | －0．05 | 37.54 | －0．04 |
|  |  | －0．03 | －0．03 | －0．02 | 0 | －0．04 | 0.05 | 0.17 | 0.05 | 0.06 | 0.01 | 0.06 | 0.03 | －0．03 |
|  |  | －0．11 | 0.03 | －0．29 | 2.39 | －0．96 | －0．02 | －0．11 | 0.78 | －0．08 | 0.07 | －0．1 | 0.51 | －0．98 |
|  |  | －0．06 | 0.01 | －0．07 | 0.04 | －0．04 | 0.01 | 0.08 | 0.02 | 0.01 | 0.01 | 0.01 | 0.05 | －0．04 |
|  |  | －0．04 | 0.03 | －0．23 | 67.41 | －0．09 | 0 | －0．04 | 0.7 | －0．03 | 0.07 | －0．06 | 76.72 | －0．01 |
|  |  | －0．06 | 0.01 | －0．01 | 0.21 | －0．01 | －0．01 | 0.08 | －0．01 | 0 | －0．04 | －0．01 | 0.22 | －0．09 |
|  |  | －0．06 | 0.04 | －0．02 | 0.07 | 0 | 0 | 0.07 | 0 | 0 | 0 | 0.02 | 0.03 | －0．04 |
|  |  | 0.01 | 0.1 | －0．24 | 3.9 | －0．95 | －0．01 | －0．09 | 1.31 | －0．05 | 0.03 | －0．13 | 16.17 | －0．89 |
|  |  | －0．12 | 0.02 | －0．34 | 2.73 | －0．99 | －0．04 | －0．13 | 1.94 | －0．1 | 0.01 | －0．17 | 1.95 | －0．99 |
|  |  | －0．02 | 0 | －0．07 | 0.55 | －0．04 | －0．02 | 0.04 | －0．01 | －0．03 | 0.02 | 0.02 | 0.99 | －0．03 |
| Absol | average | 0.06 | 0.03 | 0.14 | 12.51 | 0.32 | 0.02 | 0.09 | 0.52 | 0.04 | 0.03 | 0.06 | 13.42 | 0.31 |
| 200 |  | －0．04 | －0．03 | －0．20 | 0.38 | －0．07 | 0.04 | 0.03 | 0.04 | 0.03 | －0．03 | －0．09 | 0.42 | －0．06 |
|  |  | －0．03 | 0.01 | 0.02 | 0.01 | 0.00 | －0．01 | 0.08 | －0．01 | 0.00 | 0.00 | 0.04 | 0.01 | －0．02 |
|  |  | －0．11 | 0.02 | －0．27 | 4.49 | －0．03 | －0．04 | －0．10 | 0.08 | －0．05 | 0.01 | －0．12 | 4.63 | －0．04 |
|  |  | －0．02 | －0．01 | －0．07 | 0.01 | －0．03 | 0.05 | 0.11 | 0.05 | 0.05 | －0．01 | －0．01 | －0．01 | －0．05 |
|  |  | －0．03 | 0.00 | －0．24 | 6.42 | －0．04 | －0．03 | －0．07 | 0.08 | －0．04 | －0．03 | －0．13 | 9.32 | －0．06 |
|  |  | －0．04 | 0.00 | －0．02 | 0.02 | －0．01 | －0．02 | 0.06 | －0．02 | －0．01 | 0.01 | 0.04 | 0.03 | 0.00 |
|  |  | －0．03 | －0．02 | －0．05 | 0.00 | －0．03 | 0.00 | 0.06 | 0.00 | 0.00 | 0.02 | 0.04 | 0.02 | －0．01 |
|  |  | －0．06 | 0.05 | －0．25 | 5.44 | －0．01 | 0.07 | －0．01 | 0.17 | 0.05 | 0.01 | －0．13 | 5.89 | －0．03 |
|  |  | －0．01 | －0．01 | －0．34 | 55.04 | －0．06 | －0．02 | －0．13 | 0.61 | －0．03 | 0.04 | －0．14 | 57.32 | 0.00 |
|  |  | －0．05 | －0．04 | －0．10 | －0．03 | －0．06 | －0．01 | $\begin{aligned} & 0.04 \\ & 0.07 \end{aligned}$ | -0.010.11 | －0．01 | 0.02 | 0.03 | 0.04 | 0.01 |
| Absol | average | 0.04 | 0.02 | 0.16 | 7.18 | 0.03 | 0.03 |  |  | 0.03 | 0.02 | 0.08 | 7.77 | 0.03 |


| 300 | -0.07 | 0.01 | $-0.16$ | 0.04 | 0.00 | 0.01 | 0.00 | 0.02 | 0.01 | 0.00 | -0.06 | 0.02 | -0.01 |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | -0.03 | -0.03 | -0.02 | -0.02 | -0.03 | 0.04 | 0.13 | 0.04 | 0.05 | -0.03 | 0.02 | -0.03 | -0.05 |
|  | -0.05 | 0.04 | -0.24 | 0.72 | 0.01 | -0.01 | -0.08 | -0.01 | -0.03 | 0.03 | -0.10 | 1.09 | 0.01 |
|  | 0.03 | 0.02 | -0.05 | 0.03 | 0.00 | 0.01 | 0.05 | 0.01 | 0.01 | 0.00 | 0.01 | 0.01 | -0.01 |
|  | -0.05 | -0.01 | $-0.25$ | 0.30 | -0.04 | -0.02 | -0.07 | -0.02 | -0.03 | 0.01 | -0.10 | 0.14 | -0.01 |
|  | -0.02 | -0.01 | -0.03 | -0.01 | -0.02 | 0.04 | 0.11 | 0.04 | 0.04 | -0.01 | 0.02 | 0.00 | -0.02 |
|  | -0.05 | -0.01 | -0.04 | -0.01 | -0.02 | 0.00 | 0.06 | 0.00 | 0.00 | -0.05 | -0.02 | -0.04 | -0.06 |
|  | -0.05 | 0.01 | -0.27 | 1.27 | -0.04 | 0.02 | -0.06 | 0.03 | 0.00 | -0.02 | -0.15 | 1.57 | -0.06 |
|  | -0.04 | -0.01 | -0.36 | 18.24 | -0.08 | 0.01 | -0.11 | 0.45 | 0.01 | 0.06 | -0.14 | 26.89 | 0.01 |
|  | -0.02 | -0.01 | -0.07 | -0.01 | -0.03 | 0.00 | 0.05 | 0.00 | 0.00 | -0.02 | -0.01 | -0.01 | -0.03 |
| Absolute average | 0.04 | 0.02 | 0.15 | 2.07 | 0.03 | 0.02 | 0.07 | 0.06 | 0.02 | 0.02 | 0.06 | 2.98 | 0.03 |
| Overall absolute average | 0.60 | 0.03 | 0.15 | 7.32 | 0.23 | 0.02 | 0.08 | 0.38 | 0.27 | 0.03 | 0.07 | 7.85 | 0.22 |

Note. B indicates bootstrap and M indicates model-based standard errors.
Note. $\chi_{1}{ }^{2}$ refers to the chi-squared distribution with one degree of freedom, $\mathrm{N}(0,1)$ refers to the standard normal distribution, $\mathrm{t}(3)$ refers to the t -distribution with 3 degrees of freedom, $\ln (\operatorname{unif}(1100))$ refers to a log-uniform distribution with bounds of 1 and 100 , and $\operatorname{Exp}(n o r m a l(0,1)$ refers to the exponential of the standard normal distribution.

Table A4
Power to detect path coefficients under bootstrap-based approaches.


Note. $\chi_{1}{ }^{2}$ refers to the chi-squared distribution with one degree of freedom, $N(0,1)$ refers to the standard normal distribution, $t(3)$ refers to the $t$-distribution with 3 degrees of freedom, $\ln (u n i f(1100)$ ) refers to a log-uniform distribution with bounds of 1 and 100 , and $\operatorname{Exp}(n o r m a l(0,1))$ refers to the exponential of the standard normal distribution.

```
library(MASS)
library(lavaan)
## Example Correlation/covariance matrix for variables
sigma<-matrix(c(
        1,.31,-.05, . 18,
    .31, 1,-.18, .39,
    -.05,-.18, 1,-.21,
    .18,.39,-.21, 1
    ),C(4,4))
##number of bootstrap replications
nboot<-500
##sample size for illustration
n<-100
##set seed to reproduce example dataset
set.seed(914)
##generate latent variables based on correlation and assumption of normality
d<-data. frame (mvrnorm(n=n,mu=c(0,0,0,0),Sigma=sigma))
##standardize data and apply variable names
d<-data.frame(apply(d,2,scale))
names(d)<-c("usage","addiction","support","dysreg")
##generate observed indicators of latent variables
d$al<-scale(1*d$addiction+rnorm(n))
d$a2<-scale(1.82*d$addiction+rnorm(n))
d$a3<-scale(1.25*d$addiction+rnorm(n))
d$a4<-scale(1.85*d$addiction+rnorm(n))
d$d1<-scale(1*d$dysreg+rnorm(n))
d$d2<-scale(1.37*d$dysreg+rnorm(n))
d$d3<-scale(1.27*d$dysreg+rnorm(n))
d$d4<-scale(1.49*d$dysreg+rnorm(n))
d$d5<-scale(.86*d$dysreg+rnorm(n))
d$s1<-scale(1*d$support+rnorm(n))
d$s2<-scale(1.82*d$support+rnorm(n))
d$s3<-scale(.5*d$support+rnorm(n))
#####################################
##true relationships among latent variables
truesem<- '
    addiction~ usage+dysreg+support
    usage~ dysreg+support
    dysreg~support
'
tsem<- sem(truesem,data=d,std.ov=T)
summary(tsem)
##true sequential mediation effect S-D-U-A
coef(tsem) ["dysreg~support"]*coef(tsem) ["usage~dysreg"]*coef(tsem)["addiction
~usage"]
##specify SEM
```

```
semodel<- '
    fa=~ NA*a1+a2+a3+a4
    fa ~~ 1*fa
    fd=~ NA*d1+d2+d3+d4+d5
    fd ~~1*fd
    fs=~ NA*s1+s2+s3
    fs ~~1*fs
    fu=~ 1*usage
    fa~ fu+fd+fs
    fu~ fd+fs
    fd~fs
    '
##estimate SEM with typical concurrent estimation of parameters
sem1<-sem(semodel,d)
summary(sem1)
##sequential mediation effect S-D-U-A under full info SEM
coef(sem1)["fd~fs"]*coef(sem1)["fu~fd"]*coef(sem1)["fa~fu"]
########### estimate SEM with BCFSPA
##step a--estimate individual measurement models
cfa_a<-cfa( 'fa=~ NA*a1+a2+a3+a4
            fa ~~ 1*fa',d)
        summary(cfa_a)
cfa_s<-cfa( 'fs=~ NA*s1+s2+s3
                fs ~~ 1*fs',d)
    summary(cfa_s)
cfa_d<-cfa( 'fd=~ NA*d1+d2+d3+d4+d5
                fd ~~ 1*fd',d)
    summary(cfa_d)
##step b--estimate factor scores and covariance
fs_a<-lavPredict(cfa_a,method="regression")
fs_s<-lavPredict(cfa_s,method="regression")
fs_d<-lavPredict(cfa_d,method="regression")
fscov<-((n-1)/n)*cov(data.frame(fs_a,fs_d,fs_s,d$u))
##step c--estimate corrected covariance
bcfscov<-fscov
#divide covariances by factor score and loading matrices
bcfscov[1,]<-bcfscov[,1]<-
bcfscov[1,]/(attr(lavPredict(cfa_a,method="regression",fsm=T),"fsm")[[1]] %*%
lavInspect(cfa_a,what="est") $lamb}da
bcfscov[2,]<-bcfscov[,2]<-
bcfscov[2,]/(attr(lavPredict(cfa_d,method="regression",fsm=T),"fsm")[[1]] %*%
lavInspect(cfa_d,what="est") $lam\overline{b}da)
bcfscov[3,]<-bcfscov[,3]<-
bcfscov[3,]/(attr(lavPredict(cfa_s,method="regression",fsm=T),"fsm")[[1]] %*%
lavInspect(cfa_s,what="est") $lambda)
```

```
# correct variances (fixed to one in standardized approach)
diag(bcfscov)<-1
##step d--estimate path model with corrected covariance
pathmodel<- '
    fa~ d.u+fd+fs
    d.u~ fd+fs
    fd~fs
    '
bcfspal<-sem(pathmodel,sample.cov=bcfscov,sample.nobs=n)
summary(bcfspa1)
##sequential mediation effect S-D-U-A under BCFSPA
coef(bcfspa1)["fd~fs"]*coef(bcfspa1)["d.u~fd"]*coef(bcfspa1)["fa~d.u"]
##differences among sequential mediation estimates
#Full info SEM
(coef(sem1)["fd~fs"]*coef(sem1)["fu~fd"]*coef(sem1)["fa~fu"]-
(coef(tsem)["dysreg~support"]*coef(tsem)["usage~dysreg"]*coef(tsem)["addictio
n~usage"]))/
(coef(tsem)["dysreg~support"]*coef(tsem)["usage~dysreg"]*coef(tsem)["addictio
n~usage"])
#BCFSPA
(coef(bcfspa1)["fd~fs"]*coef(bcfspa1)["d.u~fd"]*coef(bcfspa1)["fa~d.u"]-
(coef(tsem)["dysreg~support"]*coef(tsem)["usage~dysreg"]*coef(tsem)["addictio
n~usage"]))/
(coef(tsem)["dysreg~support"]*coef(tsem)["usage~dysreg"]*coef(tsem)["addictio
n~usage"])
################################################################
##
## call function from lavaan to implement each of these steps
fsrl<-fsr(semodel,d,fsr.method = "Croon", fs.method = "Regression")
fsr1
##
#############################
###############################################################
##bootstrap
#initalize vectors for each path
semaboot<-NULL
sembboot<-NULL
semcboot<-NULL
semdboot<-NULL
semeboot<-NULL
semfboot<-NULL
semMedboot<-NULL
fsraboot<-NULL
fsrbboot<-NULL
fsrcboot<-NULL
fsrdboot<-NULL
fsreboot<-NULL
fsrfboot<-NULL
fsrMedboot<-NULL
```

```
#bootstrap
for ( boot in 1:nboot) {
#sample with replacement and reestimate models
    dboot<-d[sample(1:n,n,replace=T),]
    sem1boot<-try(sem(semodel,dboot), silent=T)
    fsrlboot<-try(fsr(semodel,dboot,fsr.method = "Croon", fs.method =
"Regression"),silent=T)
#Save results for each replication
    semaboot<-c(semaboot,ifelse(class(sem1boot)[1]=="try-
error",NA,parameterEstimates(sem1boot)[22,"est"]))
    sembboot<-c(sembboot,ifelse(class(sem1boot)[1]=="try-
error",NA,parameterEstimates(sem1boot)[19,"est"]))
    semcboot<-c(semcboot,ifelse(class(sem1boot)[1]=="try-
error",NA,parameterEstimates(sem1boot)[21,"est"]))
    semdboot<-c(semdboot,ifelse(class(sem1boot)[1]=="try-
error",NA,parameterEstimates(sem1boot)[18,"est"]))
    semeboot<-c(semeboot,ifelse(class(sem1boot)[1]=="try-
error",NA,parameterEstimates(sem1boot)[20,"est"]))
    semfboot<-c(semfboot,ifelse(class(sem1boot)[1]=="try-
error",NA,parameterEstimates(sem1boot)[17,"est"]))
    semMedboot<-c(semMedboot,ifelse(class(sem1boot)[1]=="try-error",NA,
    parameterEstimates(sem1boot)[22,"est"]*parameterEstimates(sem1boot)[20,
"est"]*parameterEstimates(sem1boot)[17,"est"]
                    ))
    fsraboot<-c(fsraboot,ifelse(class(fsr1boot)[1]=="try-
error",NA,fsr1boot$PE$est[6]))
    fsrbboot<-c(fsrbboot,ifelse(class(fsr1boot)[1]=="try-
error",NA,fsr1boot$PE$est[3]))
    fsrcboot<-c(fsrcboot,ifelse(class(fsr1boot)[1]=="try-
error",NA,fsr1boot$PE$est[5]))
    fsrdboot<-c(fsrdboot,ifelse(class(fsr1boot)[1]=="try-
error",NA,fsr1boot$PE$est[2]))
    fsreboot<-c(fsreboot,ifelse(class(fsr1boot)[1]=="try-
error",NA, fsr1boot$PE$est[4]))
    fsrfboot<-c(fsrfboot,ifelse(class(fsr1boot)[1]=="try-
error",NA,fsr1boot$PE$est[1]))
    fsrMedboot<-c(fsrMedboot,ifelse(class(fsr1boot)[1]=="try-error",NA,
                    fsr1boot$PE$est[6]*fsr1boot$PE$est[4]*fsr1boot$PE$est[1]
                    ))
}
\#\#estimated standard error for each path
```

```
sd(semaboot,na.rm=T)
```

sd(semaboot,na.rm=T)
sd(sembboot, na.rm=T)
sd(semcboot,na.rm=T)
sd(semdboot,na.rm=T)
sd(semeboot,na.rm=T)
sd(semfboot,na.rm=T)

```
```

sd(fsraboot,na.rm=T)
sd(fsrbboot,na.rm=T)
sd(fsrcboot,na.rm=T)
sd(fsrdboot,na.rm=T)
sd(fsreboot,na.rm=T)
sd(fsrfboot,na.rm=T)
\#\#estimated standard error for sequential mediation effect
sd(semaboot*semeboot*semfboot,na.rm=T)
sd(fsraboot*fsreboot*fsrfboot,na.rm=T)
\#\#estimated 95% bootstrapped confidence intervals for each path
quantile(semaboot,probs=c(.025,.975))
quantile(sembboot,probs=c(.025,.975))
quantile(semcboot,probs=c(.025,.975))
quantile(semdboot,probs=c(.025,.975))
quantile(semeboot,probs=c(.025,.975))
quantile(semfboot,probs=c(.025,.975))
quantile(fsraboot,probs=c(.025,.975))
quantile(fsrbboot,probs=c(.025,.975))
quantile(fsrcboot,probs=c(.025,.975))
quantile(fsrdboot,probs=c(.025,.975))
quantile(fsreboot,probs=c(.025,.975))
quantile(fsrfboot,probs=c(.025,.975))
\#\#estimated 95% bootstrapped confidence intervals for sequential mediation
effect
quantile(semaboot*semeboot*semfboot,probs=c(.025,.975))
quantile(fsraboot*fsreboot*fsrfboot,probs=c(.025,.975))

```

\section*{Appendix B. Example \(R\) code with generated data}

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[^0]:    E-mail address: ben.kelcey@gmail.com.

