

Running Head: EMERGENT QUANTITATIVE ANALYSES

A Review of some Emergent Quantitative Analyses in Sport and Exercise Psychology

## 1 Abstract

2 The purpose of this manuscript is to provide a review of some key quantitative methods that are  
3 relevant to contemporary quantitative research in sport and exercise psychology. To achieve this  
4 purpose we provide a critical review of four quantitative methods that we believe are emergent in  
5 the sport and exercise psychology literature. The first quantitative method reviewed is sample  
6 size determination and power estimation in structural equation modelling (e.g., Satorra & Saris,  
7 1985). The second quantitative method reviewed is exploratory structural equation modelling  
8 (Asparouhov & Muthén, 2009). The third quantitative method reviewed is mixture modelling  
9 (e.g., McLachlan & Peel, 2000). The final quantitative method reviewed is Bayesian structural  
10 equation modelling (e.g., Muthén, & Asparouhov, 2012). We begin each review with an  
11 overview of the methodology, followed by a summary of one or more related applications in  
12 sport and exercise psychology research, and conclude with some ideas for possible future  
13 applications in sport and exercise psychology.

14 *Keywords:* exploratory structural equation modelling, mixture modelling, Bayesian  
15 estimation, sample size determination, power estimation

16 A Review of some Emergent Quantitative Analyses in Sport and Exercise Psychology

17 The domain of quantitative methods is constantly evolving and expanding. This means  
18 that there is tremendous pressure on researchers to stay current, both in terms of best  
19 practices and improvements in more traditional methods as well as increasingly complex  
20 new methods (Hancock, 2016, Description section, para 3).

21 One of the many and constant challenges academics face is to stay up to date with recent  
22 developments in statistical analyses that have implications for measurement and theory in their  
23 field. Researchers in sport and exercise psychology (SEP) are not spared of this challenge. Over  
24 the last 20 years or so, there has been a considerable expansion in the number of statistical  
25 techniques and software available to address questions of substantive and applied importance for  
26 the field of SEP. In our anecdotal experience, academics in this field (and most probably in other  
27 fields) tend to adopt one of the following three responses to this challenge. Some academics  
28 choose (for various reasons) not to keep up with the latest statistical developments and seek  
29 collaborators who have statistical expertise to apply these new methods. Other academics  
30 (probably the majority) try to keep up with developments in some analytical techniques due to a  
31 particular interest (e.g., in scale development). A third group of SEP researchers develop  
32 primarily a methodological expertise and reputation by being at the forefront of applying to their  
33 field numerous statistical innovations from applied statistics and psychology.

34 Although the merits of each profile can be debated, this discussion is not of interest for  
35 this paper. Instead, in this paper we aim to present in a succinct fashion some recent  
36 developments in quantitative analysis by targeting those academics in the first and second  
37 profile. We hope that our introduction to a selection of emerging quantitative analyses and a brief  
38 overview of their current applications in the SEP literature will trigger the curiosity and intrinsic

39 interest of a greater pool of researchers to learn more about and apply these methods. Resources  
40 exist (see citations in the following sections) which provide detailed treatments of these topics,  
41 supplemented by software code. Notably, a recent book by Ntoumanis and Myers (2016)  
42 demonstrates the applications of these methods in sport and exercise science research.

43         A review of problematic and emergent quantitative and qualitative methods by Biddle,  
44 Markland, Gilbourne, Chatzisarantis, and Sparks (2001) was seminal and highly cited in the SEP  
45 field. However, there have been many advances in quantitative methodology since that paper.  
46 During the last 10-15 years, journal article contributions in the SEP field have focused on a  
47 detailed treatment of one particular statistical technique (e.g., Myers, Martin, Ntoumanis,  
48 Celimli, & Bartholomew, 2014, presented exploratory bi-factor analysis; Fitzpatrick, Gareau,  
49 Lafontaine, & Gaudreau, 2016, discussed dyadic data analysis using the Actor-Partner  
50 Interdependence Model). In this paper we aim to provide a concise update (as far as quantitative  
51 analyses are concerned) to Biddle and colleagues seminal paper by presenting four emergent  
52 analyses, namely 1) sample size determination and power estimation in structural equation  
53 modelling, 2) exploratory structural equation modelling, 3) mixture modelling, and 4) Bayesian  
54 structural equation modelling. We begin each section with an overview of the methodology,  
55 followed by a brief overview highlighting one or more key applications within SEP, and  
56 conclude with some suggestions for future applications. The section on sample size  
57 determination deviates from the other sections in that it presents a brief demonstration of the  
58 technique. This approach was undertaken in response to Schweizer and Furley (2016) who urged  
59 researchers in the sport and exercise field to do better with regard to sample size  
60 determination/power.

61 Papers utilising these four techniques in SEP research have emerged over the last five  
62 years or so, but their applications remain relatively sparse. We chose these four quantitative  
63 analyses for a variety of reasons, such as having a pragmatic length review as an end-product for  
64 a journal article, and because these methods can provide answers to many questions from a broad  
65 spectrum of research within SEP. This focus is not to imply that other emerging statistical  
66 techniques not covered in this review are ‘inferior’ in any way. Further, our review of each type  
67 of analyses is not meant to be exhaustive as our purpose was simply to highlight one or more key  
68 SEP examples for readers.

### 69 **Sample Size Determination and Power Estimation in Structural Equation Modelling**

70 Published applications of structural equation modelling (SEM) have been relatively  
71 common in original research within SEP for some time (e.g., Biddle, Markland, Gilbourne,  
72 Chatzisarantis, & Sparkes, 2001). Rarely, however, do published applications of SEM in SEP  
73 report a power analysis (Myers, Celimli, Martin, & Hancock, 2016). Providing results from a  
74 power analysis for an application of SEM is important because doing so ‘...may improve the  
75 methodological approach within a particular study and, perhaps more importantly, may  
76 positively influence the quality of related studies in the future...’ (Myers, Celimli, Martin, &  
77 Hancock, 2016, p. 281). The purpose of this section, therefore, is to review some key approaches  
78 to power analysis in SEM that are relevant to, but have yet to become commonly implemented  
79 in, contemporary quantitative original research in SEP. To achieve this purpose we provide a  
80 brief review of two types of power analysis (i.e., sample size determination; power estimation)  
81 for two different purposes (i.e., regarding model-data fit; regarding focal parameters) as  
82 implemented in a variety of available tools (e.g., tables; online utilities; software). Before  
83 providing this review, however, a few *key terms* are defined.

84            *Statistical power* can be defined as the probability of rejecting a false null hypothesis.  
85 While the utility of null hypothesis significance testing (NHST) has been debated in statistics  
86 (e.g., Wasserstein & Lazar, 2016), psychology (e.g., Cohen, 1994) and exercise science (e.g.,  
87 Zhu, 2012), ‘NHST is still the engine of statistical inference in most health and exercise  
88 sciences’ (Buchanan & Lohse, 2016, p. 131). However, effect size (i.e., the magnitude of an  
89 effect) has been (e.g., Thomas, Salazar, & Landers, 1991) and is (e.g., Kelley & Preacher, 2012)  
90 at least as important a consideration as is statistical significance.

91            A type of power analysis that occurs prior to data collection (i.e., power is fixed and an  
92 estimate of sample size is desired) is referred to in the current manuscript as *sample size*  
93 *determination*. Sample size determination can perhaps be most beneficial at the planning stage of  
94 a study when resources related to data collection are being requested and/or allocated.  
95 Unsurprisingly, sample size determination has long been advocated for in both psychology (e.g.,  
96 Cohen, 1994) and exercise science (e.g., Zhu, 2012). Given the substantial frequency of  
97 underpowered studies in SEP observed by Schweizer and Furley (2016), these authors cautioned,  
98 ‘...that researchers should take the issues of sample sizes seriously...’ and suggested that  
99 ‘...researchers should calculate adequate sample sizes a priori based on to-be expected effects...’  
100 (p. 121).

101            A type of power analysis that occurs after data have been collected (i.e., sample size is  
102 fixed and an estimate of power is desired) is referred to in the current manuscript as *power*  
103 *estimation*. Power estimation can perhaps be most beneficial for providing an empirical context  
104 within which a statistically non-significant result was observed and/or providing updated power  
105 estimates (based on the newly collected data) that can be integrated into the planning of future  
106 research. Unsurprisingly, power estimation has long been regarded as an important consideration

107 when interpreting related results of a statistical test of interest in both psychology (e.g., Cohen,  
108 1994) and exercise science (e.g., Zhu, 2012). Schweizer and Furley (2016), however, analysed  
109 manuscripts published from 2009-2013 in four prominent journals in SEP and concluded that ‘A  
110 substantial proportion of published studies does not have sufficient power to detect effect sizes  
111 for psychological research’ (p. 114). Findings from Schweizer and Furley (2016) fit within a  
112 crisis of confidence in the broader psychological quantitative literature (e.g., Hoekstra, Morey,  
113 Rouder, & Wagenmakers, 2014).

114         From this point forward the expression *power analysis* is used when referring to both  
115 sample size determination and power estimation simultaneously. Power analysis in SEM relies  
116 on three core statistical concepts – null and alternative hypotheses, test statistics to assess null  
117 hypotheses, and central and non-central distributions – which for spatial reasons are not reviewed  
118 in this manuscript. Readers are referred to Hancock and French (2013) for a thorough treatment  
119 of each of these core topics.

120         Perhaps surprisingly given the findings of Schweizer and Furley (2016), a  
121 methodological literature on power analysis in SEM for two different purposes has been  
122 available for the past few decades (e.g., MacCallum, Browne, & Sugawara, 1996; Satorra &  
123 Saris, 1985). The first purpose focuses on the entire model, which we refer to as *power analysis*  
124 *regarding model-data fit*. The second purpose focuses on one or more specific parameters within  
125 an entire model, which we refer to as *power analysis regarding focal parameters*. Both types of  
126 power analysis (i.e., sample size determination; power estimation) can be used for both purposes  
127 of a power analysis (i.e., regarding model-data fit; regarding focal parameters) and often with a  
128 variety of available tools (e.g., tables; online utilities; software). Because there is recent evidence  
129 that the field of SEP does not, on average, report power analyses in SEM in published

130 manuscripts (and thus there is not a large body of literature to review per se), we provide a few  
131 brief ‘how to’ demonstrations below.

### 132 **A Related Application with Brief Demonstrations**

133 In order to provide an overview of two types of power analysis for two different purposes  
134 as implemented in a variety of available tools, we first summarize a relevant application of SEM  
135 that we will refer to during our brief demonstrations. Myers, Park, et al. (2016) provided initial  
136 validity evidence for measuring multidimensional well-being in a Hispanic sample with the I  
137 COPPE Scale (Prilleltensky et al., 2015). More specifically, Myers, Park, et al. reported evidence  
138 that the measurement theory for responses to the I COPPE Scale emerged in an exploratory bi-  
139 factor analysis (under target rotation) and that the I COPPE subjective well-being factors  
140 exhibited convergent relations with scores from theoretically relevant comparison instruments.  
141 Figure 1 depicts standardized parameter estimates that are commonly of primary interest (i.e., 39  
142 pattern coefficients and 7 correlation coefficients) from Myers, Park, et al.

143 The brief demonstrations provided below are intended to display a reasonable way to  
144 proceed in many applications of SEM in SEP. Some decisions are made, however, for the sake of  
145 textual parsimony and should be altered as justified within subsequent applications in practice.  
146 Type I error rate is set to  $\alpha = .05$  and power is set to .80. Assumptions, too, are made about the  
147 model to be imposed (e.g., at least close model-population data fit), the data to be analysed (e.g.,  
148 conditionally multivariate normal), and the estimation method that will be used (i.e., maximum  
149 likelihood). Readers are referred to Hancock and French (2013) for a thorough treatment of each  
150 of these assumptions.

151 Degrees of freedom are determined for the full model that is only partially depicted in  
152 Figure 1 by subtracting the number of parameters to be estimated ( $q$ ) from the number of



153 observations available for the analysis ( $u$ ). Given that the means are assumed to be in the model,  
154  $u$  can be determined by finding the value of:  $p(p+3)/2$ , where  $p$  is the number of observed  
155 variables. Therefore, the value of  $u$  is 434 (i.e.,  $28(28+3)/2$ ). The value of  $q$  can be determined by  
156 summing the number of parameters to be estimated in the model. For example, specific  
157 parameters for the measurement model are as follows: 21 intercepts (i.e., one for each item), 126  
158 pattern coefficients or ‘loadings’, 21 residual variances (i.e., one for each item) and 63 residual  
159 covariances; whereas specific parameters for the latent variable model are as follows: 7 means  
160 (i.e., one for each latent variable), 7 variances (i.e., one for each latent variable) and 70  
161 covariances.<sup>1</sup> Therefore, the value of  $q$  is 315. The value of  $df$  is 119 (i.e.,  $434-315$ ).

162       **Brief Demonstration 1.** This demonstration is intended to be applicable to future  
163 research (and particularly prior to data collection) in SEP when, in general, ‘type’ = sample size  
164 determination, ‘purpose’ = model-data fit, and ‘tool’ = table(s). In such cases, the necessary  
165 inputs to be provided by the user include:  $\alpha$ -level,  $df$  for the entire model, desired level of power,  
166 a population model-data fit value for the null condition and a population model-data fit value for  
167 the alternative condition. To demonstrate, sample size is determined (for a given power value)  
168 regarding model-data fit for the Myers, Park, et al., (2016) example using the tables (e.g., Table  
169 4.1 on p. 128) provided in Hancock and French (2013).<sup>2</sup> A value of population model-data fit  
170 (i.e.,  $\varepsilon$ ) in the root mean square error of approximation (i.e., RMSEA; Steiger & Lind, 1980)  
171 metric is specified as .05 for the null condition (i.e.,  $\varepsilon_0$ ). Two values of population model-data fit  
172 in the RMSEA metric are specified, .02 and .04, for the alternative condition (i.e.,  $\varepsilon_1$ ) consistent  
173 with the 90% confidence interval, [.018, .035], reported in Myers, Park, et al. Degrees of  
174 freedom for the entire model are rounded to 120 (from 119, as calculated above). Therefore,  
175 necessary sample size is equal to 191 when  $\varepsilon_1 = .02$  and 702 when  $\varepsilon_1 = .04$ . Readers are referred

176 to Hancock and French (2013) for more detailed step-by-step demonstrations of power analysis  
177 in SEM via tables.

178         **Brief Demonstration 2.** This demonstration is intended to be applicable to future  
179 research (and particularly after data collection) in SEP when, in general, ‘type’ = power  
180 estimation, ‘purpose’ = model-data fit, and ‘tool’ = online utility. In such cases, the necessary  
181 inputs to be provided by the user include:  $\alpha$ -level,  $df$  for the entire model, sample size, a  
182 population model-data fit value for the null condition and a population model-data fit value for  
183 the alternative condition. To demonstrate, power is estimated (for a given sample size value)  
184 regarding model-data fit for the Myers, Park, et al., (2016) example using an online utility  
185 provided by Preacher and Coffman (2006) at <http://quantpsy.org/rmse/rmse.htm>. Population  
186 model-data fit values are identical to those specified in the previous paragraph. Degrees of  
187 freedom for the entire model are 119 because rounding is unnecessary in the online utility. A  
188 range of sample size values is specified (i.e., 250, 500, and 1000), consistent with relevant  
189 recommendations (e.g., Myers, Ahn, & Jin, 2011). When  $\epsilon_1 = .02$ , power estimation is equal to  
190 .93 when sample size equals 250 and it approximates 1.00 when sample size equals 500 or 1000.  
191 When  $\epsilon_1 = .04$ , power estimation is equal to .33 when sample size equals 250; .63 when sample  
192 size equals 500; and, .93 when sample size equals 1000. Readers are referred to Myers, Celimli,  
193 et al. (2016) for more detailed step-by-step demonstrations of power analysis in SEM via  
194 Preacher and Coffman’s (2006) online utility.

195         **Brief Demonstration 3.** This demonstration is intended to be applicable to future  
196 research (and particularly after data collection) in SEP when, in general, ‘type’ = power  
197 estimation, ‘purpose’ = focal parameter(s), and ‘tool’ = software. In such cases (and under the  
198 user-friendly approach to be demonstrated), the necessary inputs to be provided by the user

199 include: a dataset, a model, a population value for each focal parameter,  $\alpha$ -level, and sample  
200 size. To demonstrate, power is estimated (for a given sample size value) regarding focal  
201 parameters for the Myers, Park, et al., (2016) example using Monte Carlo methods for a real data  
202 analysis via a two-step approach implemented in *Mplus* 7.4 (Muthén & Muthén, 1998-2015).<sup>3</sup>  
203 Suppose that the 39 pattern coefficients and the 7 correlation coefficients depicted in Figure 1 are  
204 the focal parameters and that  $\theta_i$  is used to symbolize a particular focal parameter. Monte Carlo  
205 methods can be used to determine the proportion of replications at which each  $H_0 : \theta_i = 0$  is  
206 rejected for a particular sample size. A range of sample size values is specified: 250, 500, 1000.  
207 The number of replications is set to 10,000. The vast majority of parameter estimates for the  
208 entire model from Myers, Park, et al. were treated as population values.<sup>4</sup> The smallest power  
209 estimation value across all focal parameters is equal to .986 (i.e., covariance of interpersonal  
210 well-being with interpersonal comparison measure) when sample size equals 250 and 1.00 when  
211 sample size equals 500 or 1000.

212 Appendix A and Appendix B provide annotated input for Step 1 and Step 2,  
213 respectively.<sup>5</sup> Note that this code could also be used to determine sample size (for a given power  
214 value) regarding focal parameters. Appendix C provides truncated output identifying the power  
215 estimation value for each focal parameter when sample size equalled 250. Appendix D provides  
216 a simulated dataset (download file named *dem\_3.txt*) so that readers can try running the syntax  
217 provided in Appendix A and Appendix B themselves.<sup>6</sup> Readers are referred to Muthén and  
218 Muthén (2002), Myers, Ahn, et al. (2011), and to Paxton, Curran, Bollen, Kirby and Chen (2001)  
219 for more detailed step-by-step demonstrations of power analysis in SEM via Monte Carlo  
220 methods with software. Readers are referred to Muthén and Muthén (2002) for a demonstration

221 of how missing data and non-normal data may be accommodated in a power analysis in SEM via  
222 Monte Carlo methods with software.

### 223 **Future Directions**

224 Both the potential utility, and the relatively infrequent observation of, power analysis in  
225 SEM for original research in SEP have been known for some time (e.g., Biddle et al., 2001).  
226 Since the contribution of Biddle et al. (2001), however, a variety of progressively more  
227 accessible ‘how-to’ resources have been made available in an effort to increase the frequency of  
228 power analysis in SEM across disciplines for both types (i.e., sample size determination; power  
229 estimation) and both purposes (i.e., regarding model-data fit; regarding focal parameters) and  
230 with a variety of tools: tables (e.g., Hancock & French, 2013), online utilities (e.g., Preacher &  
231 Coffman, 2006), and software (e.g., Muthén & Muthén, 2002). The routine application of power  
232 analysis in SEM (and in other statistical modelling frameworks) for original research in SEP,  
233 however, has yet to fully emerge (e.g., Schweizer & Furley, 2016). The review, and the brief  
234 demonstrations of, power analysis in SEM provided in this manuscript (i.e., Brief Demonstration  
235 1: sample size determination regarding model-data fit with a table; Brief Demonstration 2: power  
236 estimation regarding model-data fit with an online utility; Brief Demonstration 3: power  
237 estimation regarding focal parameters with software) should be viewed as an additional effort to  
238 expedite the full emergence of power analysis in SEM for contemporary quantitative original  
239 research in SEP. The expression ‘full emergence of power analysis in SEM’ should not be  
240 equated with the suggestion of a ‘golden rule’ that all studies in SEP that use SEM must report a  
241 power analysis as clearly there may be some cases where sufficient information is not available.

## 242 **Exploratory Structural Equation Modelling**

### 243 **An Overview**

244 Exploratory structural equation modelling (ESEM) was first proposed by Asparouhov  
245 and Muthén (2009). ESEM integrates exploratory factor analysis (EFA), independent clusters  
246 model confirmatory factor analysis (ICM-CFA) and structural equation modelling (SEM). ESEM  
247 can have an exploratory or confirmatory focus, depending on the research objectives of a study.  
248 Although ICM-CFA has typically been considered superior to EFA due to its greater parsimony  
249 and integration to the overarching SEM framework, recent research evidence has shown that  
250 forcing cross-loadings to be exactly zero tends to be overly restrictive for applied research. In  
251 contrast, using EFA typically accommodates such cross-loadings, particularly if they are small in  
252 size (Kline, 2000). ESEM allows the testing of such cross-loadings whilst at the same time  
253 preserving the advantages associated with ICM-CFA (e.g., path coefficients corrected for  
254 measurement error, testing of invariance of factor structure over time and/or groups). As noted  
255 by Asparouhov, Muthén, and Morin (2015), allowing cross-loadings does not undermine  
256 constructs by adding ‘noise’ but rather allows them to be estimated using all of the relevant  
257 information. Nevertheless, researchers should always aim to develop instruments that have small  
258 rather than large cross-loadings. It should also be noted that no cross-loadings should be allowed  
259 between factors which predict one another as this undermines the assumption of directionality of  
260 the associations.

261 By allowing cross-loadings on one or more factors, ESEM addresses important  
262 limitations associated with ICM-CFA. Specifically, by constraining cross-loadings to zero, ICM-  
263 CFA will result in inflated factor correlations; typically, the higher the magnitude of the cross-  
264 loadings, the greater the inflation in factor correlations (Marsh, Lüdtke, Nagengast, Morin, &  
265 VonDavier, 2013). As a result, positively biased and artificially inflated correlations undermine  
266 the discriminant validity of a multidimensional instrument and the predictive validity of its

267 factors, due to multicollinearity (Marsh, Morin, Parker, & Kaur, 2014). Many instruments in SEP  
268 have correlated factors, hence, the use of ESEM is recommended to address this problem.

269 ESEM can be used when an instrument has two or more factors (because with a single-  
270 factor model there are no cross-loadings). ICM-CFA is nested under ESEM (Morin, Marsh, &  
271 Nagengast, 2013), hence the fit of the two models (and the plausibility of parameter estimates)  
272 can be compared as with any nested models (e.g., a chi-square difference test). Marsh et al.  
273 (2014) recommended that both ICM-CFA and ESEM models should be tested with the same data  
274 set; if the fit of both types of models is equivalent, the ICM-CFA model should be preferred as it  
275 is more parsimonious. However, Marsh et al. observed that the ICM-CFA is often too restrictive  
276 to provide acceptable fit for most psychological instruments; this is also the case in the field of  
277 SEP, as our brief review below indicates. It is also possible to include sets of ESEM and CFA  
278 factors in the same model.

279 One limitation of ESEM is that the pattern of cross-loadings and the size of the factor  
280 correlations will vary depending on the rotation method utilised (Morin et al., 2013). Examining  
281 model fit cannot help with this problem as fit indices are identical under different rotation  
282 methods. Marsh, Lüdtke, et al. (2013) recommended that the results of different estimation  
283 methods be compared. The online supplements accompanying the Morin, Marsh and Nagengast  
284 (2013) chapter suggested the potential for problems with geomin rotation in Mplus with a default  
285 epsilon value when using simulated data. In Table 1, we present the rotation method used in  
286 different ESEM studies in the SEP literature (and encourage the reporting of epsilon value(s) in  
287 future studies that use geomin rotation). In practice, the use of target rotation has been recently  
288 favored in the literature as providing a way to rely on a more confirmatory approach to the  
289 estimation of EFA factors (e.g., Myers, Jin, Ahn, Celimli, & Zopluoglu, 2015). With target

290 rotation, researchers indicate the approximate size of expected cross-loadings. It should be noted,  
291 however, that this practice is appropriate when ESEM is used in a more confirmatory mode, in  
292 other words, when researchers have clear views of the factor structure expected. If neither ICM-  
293 CFA nor ESEM produces acceptable model fit, or if researchers do not have a clear view of the  
294 expected factor structure, ESEM can be used in an exploratory fashion (e.g., see Payne, Hudson,  
295 Akehurst, & Ntoumanis, 2013).

296 An advantage of ICM-CFA over EFA is the flexibility to examine the measurement  
297 invariance and compare latent means across groups and/or over time. Such an advantage is  
298 preserved under an ESEM framework. Readers are directed to Table 1 presented in Marsh et al.  
299 (2014) for a list of 13 tests of invariance that can be examined within ESEM (see also  
300 Schellenberg et al., 2014). However, unlike with ICM-CFA, some types of partial factor  
301 invariance cannot be tested via ESEM. Specifically, it is not possible to test partial invariance of  
302 factors loadings, variances, and covariances (or to separate tests of invariance of factor variances  
303 from those of factor covariances). However, it is possible to pursue tests of partial invariance of  
304 intercepts (or thresholds), uniqueness, and latent means. Therefore, Marsh, Nagengast and Morin  
305 (2013) proposed ESEM-within-CFA framework as a solution to address this problem. This  
306 technique also enables the testing of models not possible under ESEM, such as higher-order  
307 factor models, latent curve models, or models in which some but not all factors are related to  
308 other variables (e.g., demographics), or mediation models with bootstrapped confidence intervals.  
309 The readers are referred to Morin, Marsh, and Nagengast (2013) for more information on how  
310 ESEM-within-CFA can deal with such limitations of ESEM.

### 311 **Related Applications**

312 Applications of ESEM have grown substantially since the initial paper by Asparouhov  
313 and Muthén (2009). A search on the Scopus database in September 2016 indicated more than  
314 200 articles utilising this method, with nearly 10% of them in the area of SEP (see Table 1 for an  
315 overview of select ESEM applications in SEP). Some researchers in the SEP field have utilised  
316 ESEM to test the factor structure of responses to a new questionnaires. For example, Appleton,  
317 Ntoumanis, Quested, Viladrich, and Duda (2016) developed and validated a new questionnaire  
318 that assesses young athletes' perceptions of the coaching environment, as proposed by  
319 achievement goal theory and self-determination theory (the Empowering and Disempowering  
320 Motivational Climate Questionnaire-Coach; EDMCQ-C). Drawing from various questionnaires,  
321 the authors pulled together an item pool which they then reduced by comparing alternative factor  
322 structures via ESEM, bi-factor ESEM, and ICM-CFA. A target rotation was utilised and  
323 hierarchical structures were compared using ESEM-Within-CFA and bi-factor ESEM  
324 approaches. Overall, ESEM solutions produced a better fit compared to ICM-CFA solutions,  
325 with bi-factor ESEM providing the best fit. However, some of the parameter estimates and  
326 obtained factor structures via ESEM did not conform to the theory underpinning the EDMCQ-C.  
327 The authors concluded that further work on the questionnaire was needed.

328 Other authors have used ESEM to adapt existing questionnaires. For example, Morin et  
329 al., (2016) tested a revised version of the short Physical Self-Inventory (PSI-S; Morin & Maiano,  
330 2011) which included positively-worded reformulations of the original negatively-worded items.  
331 Morin et al. showed that scores from the revised PSI-S were invariant amongst samples of  
332 English and French-speaking adolescents. When compared to ICM-CFA, the ESEM produced  
333 better model fit and more orthogonal factors. For the ESEM, the authors used a target rotation in  
334 a confirmatory manner, specifying six correlated factors and cross-loadings as close to zero as



335 possible. ESEM (as well as ICM-CFA) was used to show the longitudinal invariance of scale  
336 scores over a period of 7-8 months. Using a multiple-group multiple indicators multiple causes  
337 (MIMIC) approach, Morin et al. showed that the PSI-S scores showed no measurement bias in  
338 relation to gender, age, body mass index, or physical activity involvement.

339 Other authors have tested the measurement invariance of responses to a questionnaire by  
340 comparing an ICM-CFA model against an ESEM model. For example, Viladrich et al. (2013)  
341 examined the factor structure of responses to the Behavioural Regulation Sport in Questionnaire  
342 (BRSQ; Lonsdale, Hodge, & Rose, 2009) in youth soccer players from five European countries.  
343 The authors found that ESEM solutions (with target rotations) produced better model fit and  
344 lower inter-factor correlations compared to the ICM-CFA solutions. Further, ESEM-based  
345 invariance testing showed that BRSQ scores had metric invariance across the five samples.  
346 Viladrich et al. were not able to test for partial invariance as this is not possible in ESEM (unless  
347 an ESEM-within-CFA approach is implemented; see Marsh et al., 2013).

#### 348 **Future Directions**

349 It would be interesting if researchers used ESEM to revisit the factor structure of scores  
350 from questionnaires that have been previously shown to have poor fit and/or poor factor  
351 discriminant validity when tested with ICM-CFA (for examples of such an effort see Perry,  
352 Nicholls, Clough, & Crust, 2015, and Fogarty, Perera, Furst, & Thomas, 2016). ESEM can be  
353 used in testing latent growth models, multi-trait multi-method (MTMM) models, bi-factor  
354 models, as well as latent path analysis models. Researchers in SEP are encouraged to explore  
355 such possibilities as they have certain advantages compared to ICM-CFA based approaches. For  
356 example, with regard to MTMM, Marsh et al. (2014) noted that compared to ESEM solutions,  
357 ICM-CFA solutions typically provide poorer tests of discriminant validity, which is particularly

358 critical in MTMM studies. Further, a bi-factor ESEM approach (e.g., see Appleton et al. 2016 for  
359 an applications in SEP) is one way of testing factor structures within ESEM involving both a  
360 general and specific factors (see Morin, Arens, & Marsh, 2016, and Myers et al., 2014 where  
361 some distinctions are outlined between bi-factor ICM-CFA and bi-factor ESEM).

362 Bayesian structural equation modelling (BSEM; Muthén & Asparouhov, 2012) has a lot  
363 of similarities with ESEM, particularly when the target rotation is used (Marsh et al., 2014).  
364 BSEM allows cross-loadings via allowing researchers to provide estimated values based on  
365 previous research (or default software options). BSEM could be an alternative to ESEM when  
366 researchers are interested in testing higher-order factor structures or when the sample size is  
367 small relative to the complexity of the tested model. This is because Bayesian methodology does  
368 not require the normality assumption to be met, as is the case with frequentist tests such as  
369 ESEM and ICM-CFA (although with the latter it is possible to use estimation methods that take  
370 account non-normality). Researchers in SEP are encouraged to compare ESEM and BSEM  
371 approaches with the same data set (e.g., by examining the plausibility of obtained parameter  
372 estimates or whether solutions have converged with no error messages), particularly in cases  
373 where samples sizes are relatively small and instruments with numerous factors are modelled. A  
374 fuller review of Bayesian Statistics in SEP is provided in a subsequent section of this manuscript.

## 375 **Mixture Modelling**

### 376 **An Overview**

377 Researchers in SEP are often interested in examining group differences (e.g., sex) on a  
378 key variable of interest (e.g., intrinsic motivation). In this case, researchers will have an *a priori*  
379 hypothesis and therefore have collected information about a known grouping variable. However,  
380 there are times when researchers may not know if there are groups or subpopulations within their

381 data. Mixture modelling can be used to uncover subpopulations that may exist in the data that  
382 were not known *a priori* (McLachlan & Peel, 2000), which is most likely to be the case when  
383 subpopulations exist on psychosocial variables. In contrast to the example above with sex, the  
384 researcher will not have collected information about the grouping variable and instead they rely  
385 on mixture modelling to identify the unobserved subpopulations (Nylund, Asparouhov, Muthén,  
386 2007; Muthén & Muthén, 2000). These unobserved subpopulations are considered to be  
387 typological in that they provide a classification scheme and prototypical in that each participant  
388 has a given probability of membership to each subpopulation (Morin & Wang, 2016).

389 Mixture modelling is based on a *person centred approach*. The objective of a person  
390 centred approach is to examine relationships between people whereas the goal of a *variable*  
391 *centred approach* (e.g., classical SEM, regression methods) is to examine associations between  
392 variables (Morin & Wang, 2016; Muthén & Muthén, 2000). In mixture modelling, researchers  
393 identify relationships among people and classify or group them into categories called latent  
394 classes (for categorical indicators) or profiles (for continuous indicators). Given that most  
395 indicators used by SEP researchers are continuous, we will use the term ‘latent profile’ for the  
396 remainder of this section. Each latent profile contains people who are similar to each other (i.e.,  
397 homogenous within groups) and different from people in other latent profiles (i.e., heterogeneous  
398 across groups; Muthén & Muthén, 2000) at one time point or over time (Nylund et al., 2007).  
399 Latent profiles can differ quantitatively (i.e., in levels or magnitude) and/or qualitatively (i.e., in  
400 shape or combinations of variables; Morin & Wang, 2016). For example, participants can have  
401 high, medium, and low levels of *both* autonomous and controlled motivation (i.e., only  
402 quantitative differences between profiles because within profiles there is a similar magnitude of  
403 autonomous and controlled motivation). Participants could also have differing levels of *each*

404 type of motivation within one profile (e.g., profile 1 = high controlled, low autonomous  
405 motivation; profile 2 = high controlled, high autonomous motivation) and these qualitative  
406 differences within and between profiles of motivation (e.g., high/low and high/high) may lead to  
407 differential outcomes such as higher/lower physical activity participation.

408 Mixture modelling is considered to be an exploratory approach because researchers must  
409 fit several models specifying differing numbers of latent profiles in each model (Bauer & Curran,  
410 2003). Typically, combinations of statistical criteria are used to determine the best model  
411 delineating the appropriate number of latent profiles. Simulation research (see Morin & Wang,  
412 2016 for a recent review) has shown that the consistent Akaike information criterion (CAIC),  
413 Bayesian information criterion (BIC), the sample size adjusted BIC (ABIC), and the bootstrap  
414 likelihood ratio tests (bootstrap LRT), are effective for determining the number of profiles.  
415 Entropy can be used as a summary of the classification accuracy (see McLachlan & Peel, 2000;  
416 and Nylund, et al., 2007 for further details on profile enumeration). In addition, when estimating  
417 mixture models, researchers should be aware that they typically require large sample sizes and  
418 that multiple start values should be tested to ensure that the models converge on global rather  
419 than local solutions (McLachlan & Peel, 2000; Nylund et al., 2007). Alongside statistical criteria,  
420 it is important that researchers consider theory, the research question, parsimony, and the  
421 interpretability of the latent profiles (Bauer & Curran, 2003; Jung & Wickrama, 2008), as  
422 inferences made from incorrect models could cause ambiguity and erroneous conclusions  
423 (Duncan, Duncan, & Strycker, 2006; Nylund et al., 2007; Jung & Wickrama, 2008).

424 Traditionally, the specific type of mixture model invoked depended on the nature of the  
425 data (e.g., categorical or continuous) as well as the study design (e.g., cross-sectional or  
426 longitudinal). For example, within a cross-sectional design, latent class analysis (for categorical

427 variables) and latent profile analysis (for continuous variables) can be used to examine  
428 unobserved subpopulations in observed variables (Muthén & Muthén, 2000). Within a  
429 longitudinal design, latent transition analysis (for categorical indicators) and latent profile  
430 transition analysis (for continuous indicators) can be used to examine change in class or profile  
431 membership, respectively, over time (Muthén & Muthén, 2000). Still within a longitudinal  
432 framework, latent class growth analysis can be used to examine one indicator over time to  
433 determine the number of different growth curves in a population (e.g., one class may have linear  
434 change and another may have quadratic change; Muthén & Muthén, 2000). However, in latent  
435 class growth analysis, only one mean growth curve is estimated for each latent class and for this  
436 reason, researchers have recently cautioned against its use given that it can lead to biased results  
437 caused by over-extracting spurious latent classes (Diallo, Morin, Lu, 2016). In contrast to the  
438 restricted latent class growth analysis, a growth mixture model can be estimated in which the  
439 mean growth curves are random and therefore, variation around the mean is permitted (Muthén  
440 & Muthén, 2000).

441 Other emerging types of mixture models include regression mixture models and factor  
442 mixture models. Regression mixture models can be used to examine if relationships between two  
443 variables differ across profiles of people (see Morin & Wang, 2016; Morin, Scalas, & Marsh,  
444 2015). Factor mixture models combine a latent class (or profile) model with the common factor  
445 model (Lubke & Muthén, 2005). Therefore, in a factor mixture model, profiles are used to  
446 describe unobserved subpopulations whereas continuous latent factors are used to model the  
447 covariation among observed variables. Finally, generalized SEM (sometimes called general  
448 growth mixture modelling) is an extension of each of the above methods in that it allows  
449 researchers to integrate mixture modelling into a SEM framework. Therefore, using generalized

450 SEM researchers can examine antecedents or outcomes of profiles from any cross-sectional or  
451 longitudinal mixture model and also incorporate more than one type of mixture model into the  
452 same overall model (Morin & Wang, 2016; Muthén & Muthén, 2000).

### 453 **Related Applications**

454         Although variable centred analyses currently appear to be the *modus operandi* of SEP  
455 researchers, the advantages of mixture modelling and increasing ease of model estimation have  
456 led SEP researchers to employ mixture models to answer novel research questions (Morin &  
457 Wang, 2016). Table 2 provides an overview of select applications of mixture modelling in  
458 prominent SEP or related journals. For example, SEP researchers have used latent class or profile  
459 analysis to investigate if subgroups of athletes existed based on their perception of the talent  
460 development environment (Ivarsson et al., 2015) or if different profiles of exercise goal contents  
461 existed within the population (Lindwall, Weman-Josefsson, Sebire, & Standage, 2016). In the  
462 later application, Lindwall and colleagues (2016) uncovered five latent profiles of exercise goal  
463 contents that differed both quantitatively (i.e., one profile had low levels whereas another had  
464 high levels of goal contents) and qualitatively (i.e., the three remaining profiles had qualitatively  
465 different shapes/combinations of different types of goal contents).

466         Using a longitudinal design, Martinent and Nicolas (2016) first employed latent profile  
467 analysis to examine if there were different profiles of coping in sport and then conducted latent  
468 profile transition analysis to determine if athletes changed in their coping profiles over time. As a  
469 whole, they found evidence of four coping profiles over two separate time points and that there  
470 was some stability and change in these coping profiles over time (Martinent & Nicolas, 2016).  
471 Using latent class growth modelling, Gaudreau and colleagues (2009) examined if trajectories of  
472 positive and negative affect in elite adolescent hockey players changed over an 11-week period.

473 The authors found evidence of three trajectories of change in positive affect over time which  
474 they labelled as ‘high and decreasing’, ‘unstable’, and ‘medium and decreasing’. They also found  
475 three trajectories of change for negative affect over time which they labelled as ‘low and  
476 unstable’, ‘medium and unstable’ and ‘high and decreasing’.

477 Using a growth mixture model, Ventura and colleagues (2009) found four distinct  
478 trajectories in girls’ body mass index over ten years of childhood and adolescence. They also  
479 found that within each trajectory, there was individual variation such that each girl followed their  
480 own trajectory within their trajectory class. Finally, using general growth mixture modelling (or  
481 generalized SEM), Rodriguez and Audrain-McGovern (2004) identified four trajectories of  
482 change in sport participation from grade 9 to 11 and that participants in the ‘decreasing or erratic  
483 participation’ trajectory were almost three times more likely to be current smokers in grade 11  
484 compared to those in the ‘high participation’ trajectory.

#### 485 **Future Directions**

486 Mixture modelling is a rapidly developing area of statistics with advances being made  
487 annually. As mixture modelling becomes more accessible through further education (e.g.,  
488 graduate student courses, workshops), developments in computer software, and advances in  
489 mixture modelling methods, we anticipate that SEP researchers will turn more frequently to  
490 mixture modelling to answer novel research questions.

491 Advances in Bayesian mixture modelling may be useful for SEP researchers dealing with  
492 complex models and small sample sizes. The current scarcity of Bayesian mixture modelling in  
493 SEP research could stem from unfamiliarity and the added complexity of Bayesian mixture  
494 modelling. For example, Bayesian mixture modelling can lead to issues associated with latent  
495 class labels switching during estimation (i.e., ‘switching labels’; Depaoli, 2013; Asparouhov &





519 **An Overview**

520           When thinking about a new project or idea, researchers often have some degree of prior  
521 knowledge (e.g., past research findings, theory) or expectation regarding the direction (e.g.,  
522 positive or negative) and/or strength (e.g., small, moderate, large) of effects among the study  
523 variables. Armed with these expectations, a study is designed to test the idea (e.g., cross-  
524 sectional survey, experiment, intervention) and data are collected from the target population.  
525 Subsequently, these data are analysed with the view to ascertain the degree to which one's  
526 expectations or hypotheses are supported by the data. As is often the case in many scientific  
527 disciplines, including SEP (Buchanan & Lohse, 2016), the default approach to data analysis is to  
528 perform a significance test that is almost always summarised with a  $p$  value, and sometimes  
529 includes an associated effect size and/or confidence interval. Typically, the  $p$  value is the  
530 foundation of a dichotomous decision to reject or accept the null hypothesis (e.g.,  $p < .05$ ).

531           Despite the prominence in SEP research, the reliance strictly on  $p$ -values can be  
532 problematic and could lead to a misinterpretation of the results in several ways. First, using the  
533 *frequentist approach* (e.g., relying on  $p$ -values and ML), most researchers wish to know the  
534 probability that their hypothesis or theory is true given the data at hand; however, frequentist  
535 methods only provide insight into the probability of observing the same data or the probability of  
536 more extreme data, given a hypothesis or theory. Second, frequentist methods do not incorporate  
537 prior beliefs or expectations explicitly within the statistical model. Instead, frequentist methods  
538 rely on long-run frequency or a hypothetical infinite repetition of the same study in which the  
539 extremeness of the study data depends on data that were never observed. Such an approach limits  
540 the extent to which data are accumulated and synthesised over time because researchers  
541 essentially test the same null hypothesis repeatedly, while not explicitly incorporating results

542 from previous research into their analyses (van de Schoot et al., 2014). Third, within a  
543 frequentist approach, interval estimates (e.g., confidence intervals) can be misinterpreted because  
544 they do not reflect the intuitive statements that most researchers wish to make from their data  
545 (Morey, Hoekstra, Rouder, Lee, & Wagenmakers, 2016); that is, within frequentist statistics, it  
546 would be incorrect to conclude that there is a 95% chance the effect of  $x$  on  $y$  (e.g.,  $\beta = .40$ ) lies  
547 between .30 and .50. Within a frequentist framework, a confidence interval is a ‘numerical  
548 interval constructed around the estimate of a parameter’ that is a property of a particular ‘when  
549 used repeatedly across a series of hypothetical data sets (i.e., the sample space), yields intervals  
550 that contain the true parameter value in 95% of the cases’ (Hoekstra et al., 2014, p. 1159).  
551 Finally, with regard to statistical significance tests, rejecting the null hypothesis (e.g., no  
552 difference between groups) does not provide support for the alternative hypothesis (e.g.,  
553 differences between groups) because it is essentially undefined in frequentist statistics; nor does  
554 failing to reject the null hypothesis mean that the null hypothesis should be accepted (Greenland  
555 et al., 2016; Wasserstein & Lazar, 2016). As one approach for overcoming many of these issues,  
556 *Bayesian statistics* offer practical advantages for applied researchers who have an interest in  
557 parameter estimation or hypothesis testing (Wagenmakers, Morey, & Lee, 2016).

558         A summary of key differences between Bayesian and frequentist statistics is detailed in  
559 Table 3. A signature strength of Bayesian statistics is the formalisation of prior knowledge or  
560 beliefs into the statistical model through explicit statements regarding model parameters (e.g.,  
561 mean, path coefficient). Prior knowledge can encompass past empirical work (e.g., pilot data,  
562 meta-analysis) or theoretical expectations (e.g., expert knowledge, direction of the effect). The  
563 degree of (un)certainty in this knowledge is modelled via the variance of the prior distribution,  
564 and includes three broad categories of expectations: (1) non-informative prior, which captures a

565 substantial degree of uncertainty (e.g., equal probability of every value ranging from  $-\infty$  to  $+\infty$ )  
566 and therefore may not strongly influence the results (i.e., data driven findings); (2) weakly  
567 informative prior, which reflects some degree of certainty (e.g., most likely value of the target  
568 parameter, though a wide range of plausible values ranging from  $-\infty$  to  $+\infty$ ) and therefore may  
569 minimally influence the final results; and (3) informative prior, which captures a substantial  
570 degree of certainty (e.g., most likely value of the target parameter, with a small variance; van de  
571 Schoot & Depaoli, 2014; van de Schoot et al., 2014) and therefore may substantially influence  
572 the final results. With regard to psychometric examinations of questionnaires, for example,  
573 researchers can use informative priors in a confirmatory fashion to model cross-loadings with  
574 mean of zero, small variance priors, and intended factor loadings with mean and variance values  
575 that are informed by previous factor analyses or guidelines for the meaningfulness of factor  
576 loadings (e.g., Howle et al., 2016; Niven & Markland, 2016). Non-informative priors could be  
577 utilised in cases where researchers want to capitalise on the strengths of Bayesian statistics (e.g.,  
578 computationally cumbersome models with ML; Doron & Gaudreau, 2014; Tamminen et al.,  
579 2016) or where no prior knowledge exists. Finally, researchers could draw from theoretical  
580 expectations to propose weakly informative priors whereby the direction of an effect is expected  
581 alongside uncertainty regarding the strength of the association (e.g., Mahoney et al., 2014).

582         In Bayesian statistics, one's prior knowledge is combined or 'mixed' with new data to  
583 produce the posterior distribution, which provides a full summary of what is known about a  
584 parameter. For the purposes of hypothesis testing, the posterior distribution alone is unsuitable  
585 and therefore requires a comparison of the degree of belief for two competing models or  
586 hypotheses (Morey, Romeijn, & Rouder, 2016). For example, one can compare the relative  
587 plausibility of the null hypothesis (i.e., absence of an effect) with an alternative hypothesis (i.e.,

588 presence of an effect). Of interest here is the change in one's belief from before seeing the data  
589 to afterwards, which is captured in the *Bayes factor* (Morey, Romeijn et al., 2016; Wagenmakers,  
590 2007). Using a Bayes factor, the researcher can test the degree to which the data at hand are most  
591 compatible with the null or alternative hypothesis. Using a Bayes factor ( $B$ ), the researcher can  
592 test the degree to which the data at hand are most compatible with the null ( $B < 1/3$ ) or  
593 alternative hypothesis ( $B > 3$ ), or whether the data are insensitive ( $1/3 < B < 3$ ) (Dienes, 2016).  
594 Thus, unlike  $p$  values, the Bayes factor can provide evidence for the null hypothesis (Dienes,  
595 2016). For example, one might expect a zero correlation between athletic performance and the  
596 number of sporting themed movies one has watched ( $H_0$ ), whereas the alternative hypothesis  
597 ( $H_1$ ) relaxes this restriction to specify an equal probability of every value ranging from  $\pm 1$ . A  
598 comparison of the likelihood of each hypothesis being correct, given the data at hand, indicates  
599 that the observed data are 5.65 times more likely under  $H_0$  when compared with  $H_1$ . In other  
600 words, 'the data shift our prior beliefs about the relative plausibility of the competing  
601 hypotheses' by a factor of 5.65 (Wagenmakers et al., 2016, p. 171). Readers are referred  
602 elsewhere for user-friendly overviews of Bayesian statistics (Muthén & Asparouhov, 2012; van  
603 de Schoot et al., 2014; Wagenmakers et al., in press; Zyphur & Oswald, 2015), including those  
604 with a specific focus on SEP (Gucciardi & Zyphur, 2016; Stenling, Ivarsson, Johnson, &  
605 Lindwall, 2015). For a broader and comprehensive overview of the theoretical and practical  
606 underpinnings of Bayesian statistics, Etz and colleagues (in press) have produced a reading list to  
607 serve as a starting point for researchers who are new to the area.

### 608 **Related Applications**

609         The application of Bayesian statistics within the psychological sciences is on the rise (van  
610 de Schoot, Winter, Ryan, Zondervan-Zwijnenburg, & Depaoli, in press). Coinciding with this

611 increased interest, there have been several applications of Bayesian statistics within the field of  
612 SEP over the past few years. An overview of some such applications is provided in Table 4.  
613 With the exception of one study, which employed Bayesian network analysis (Constantinou et  
614 al., 2014), SEP researchers have applied Bayesian statistics for the primary purpose of parameter  
615 estimation. The majority of this work has employed BSEM to examine the factorial validity of  
616 scores from questionnaires designed to assess constructs such as commitment (Jackson et al.,  
617 2014), sport motivation (Stenling et al., 2015), walking motivation (Niven & Markland, 2016),  
618 and movement skill competence (Barnett et al., 2016). Researchers have also employed BSEM to  
619 test theoretical sequences that encompass multiple antecedent, intermediary and outcome  
620 variables, such as the relations from self-efficacy beliefs to performance on endurance-based  
621 physical activity tasks via self-presentation motives and personal task goals (Howle et al., 2016);  
622 motivational pathways informed by self-determination theory (Chan et al., 2015); and the  
623 integration of basic psychological needs and the theory of planned behaviour (Gucciardi &  
624 Jackson, 2015). Other applications of Bayesian statistics include multilevel modelling (Doron &  
625 Gaudreau, 2014; Tamminen et al., 2016), latent growth modelling (Noordstar et al., 2016), and  
626 network analysis (Constantinou et al., 2014). Within and across each of the studies, researchers  
627 have drawn from theory and past empirical work to incorporate weakly informative and  
628 informative prior information, or employed the default non-informative prior. Readers are  
629 encouraged to consult Gucciardi and Zyphur (2016) for a didactic demonstration of the  
630 application of BSEM, and those papers listed in Table 4 where the authors made available their  
631 syntax.

### 632 **Future Directions**

633           Readers who completed their educational training in psychology or the sport and exercise  
634 sciences are likely familiar with the classical approach to statistical analysis that is founded on  
635 frequentist methods (e.g.,  $p$  values). Despite being advocated as the preferred statistical approach  
636 for the psychological sciences over 50 years ago (Edwards, Lindman, & Savage, 1963), it is only  
637 in the past decade that Bayesian statistics have taken flight (van de Schoot et al., in press). With  
638 the rapid and continuous advancements in the computational capacities of computers,  
639 development of user-friendly statistical software packages (e.g., *Mplus*, JASP), and publication  
640 of didactical and primer papers (e.g., Depaoli & van de Schoot, in press), we expect Bayesian  
641 statistics to (soon) play an important role in the evolution of SEP research and practice. In  
642 addition to the possibilities outlined in Table 4 and elsewhere (van de Schoot et al., in press),  
643 Bayesian statistics can offer new insights through a range of common and uncommon analytical  
644 approaches such as evidence synthesis via meta-analysis (Scheibehenne, Jamil, & Wagenmakers,  
645 2016), sequential hypothesis testing (Schönbrodt, Wagenmakers, Zehetleitner, & Perugini, in  
646 press), analysis of single-subject designs (de Vries, Hartogs, & Morey, 2015), mixture modelling  
647 (Depaoli, 2013), and reproducibility efforts (Etz & Vandekerckhove, 2016).

648           Bayesian statistics are not without criticism. For most critics, the subjectivity of the prior  
649 is a critical concern with Bayesian statistics (e.g., Bowers & Davis, 2012). For example, two  
650 people (or research groups) may have different expectations of the study hypotheses and  
651 therefore specify different priors to be mixed with the data. As a result, these differing  
652 perspectives may result in different findings from the same data. There are at least two ways by  
653 which researchers who employ Bayesian statistics can minimise such concerns. First, as with any  
654 scientific endeavour, transparency with regard to the foundations of the priors is of central  
655 importance, both in terms of where they came from (e.g., past work, theoretical expectations)

656 and their appropriateness to be mixed with the data to make inferences with posteriors (van de  
657 Schoot et al., 2014; Zyphur & Oswald, 2015). Second, it is important that researchers conduct  
658 sensitivity analyses to ascertain the degree of influence of the priors, that is, whether or not  
659 fluctuations in background knowledge influence the stability of inferences made with posteriors  
660 (Depaoli & van de Schoot, in press). There are two broad categories of sensitivity analyses  
661 (Depaoli & van de Schoot, in press). First, weakly informative or informative priors could be  
662 compared with uninformative priors to understand the degree of subjectivity and influence on the  
663 posterior distribution. Second, weakly informative or informative priors could also be compared  
664 with varied prior distributions in which the mean and variance values are adjusted upwards or  
665 downwards to examine the influence of small to large fluctuations in prior beliefs.

#### 666 **Concluding Remarks**

667 Our intent with this manuscript was to provide a partial update to the seminal paper by  
668 Biddle and colleagues (2001) by outlining four emerging quantitative analyses that can be used  
669 by SEP researchers to answer novel research questions. Although we value the broad quantitative  
670 and qualitative approach taken by Biddle et al., we chose to review only four emergent  
671 quantitative methodologies in SEP research because we believe that our field – present authors  
672 included – may be in danger of at least occasionally ‘driving fast in reverse’ (Steiger, 2001) with  
673 regard to the application of advanced latent variable models. Most simply, we believe that while  
674 several user-friendly software programs have recently made it very easy to impose a wide variety  
675 of advanced latent variable models with a variety of estimators, an unfortunate by-product of  
676 these impressive technological developments is the increasing possibility that users may fit a  
677 complex model (and perhaps with an estimator) that they do not have a very deep understanding  
678 of (i.e., driving fast in reverse). It is hard to believe that such an approach is an optimal way to

679 efficiently advance knowledge in any discipline, however elegant the model and/or the estimator  
680 is/are. For this reason we chose to devote more text to only a few emergent quantitative analyses  
681 in SEP in hope that readers will gain at least an increased awareness of one or more of the  
682 analyses that we have reviewed. Perhaps more importantly, however, we hope that readers will  
683 gain a broader appreciation of just how much preparation it likely will take to knowingly and  
684 thoughtfully apply any advanced latent variable model. Finally, we encourage all researchers in  
685 SEP to avoid the temptation to become dogmatic about the universal implementation of a  
686 specific facet (e.g., a particular model and/or an estimator) of advanced latent variable  
687 modelling.

688         In an effort to avoid ‘driving fast in reverse’ or becoming dogmatic in approaches, we  
689 offer a few final recommendations to accelerate knowing and thoughtful applications of  
690 advanced quantitative analyses in SEP. First, in recognizing that the statistical analyses outlined  
691 are complex and potentially daunting to implement, we have provided broad overviews of each  
692 method alongside tangible applications, while also referring readers to published SEP examples  
693 with accompanying syntax. We recommend that readers consult these resources to gain an in-  
694 depth understanding of the methods and how to model them using proper syntax. To this end,  
695 although software developers continue to implement accessible syntax, we encourage readers to  
696 avoid using syntax without a deep understanding of what each key command invokes. Learning  
697 syntax is similar to learning a new language; when one begins to master the basics, the  
698 foundation for further application and extension can be easily developed. Second, readers are  
699 encouraged to actively seek opportunities for further education. Resources for students and  
700 academics alike exist. For example, if advanced statistical courses are not offered within one’s  
701 department, opportunities to take courses in related departments (e.g., education, psychology)



702 can be sought. There are also many accessible workshops offered around the world, conferences  
703 frequently offer workshops or symposiums, courses are available online, and text books  
704 represent an excellent resource for self-guided learning. It is our hope that our brief overview of  
705 emergent quantitative analyses in SEP has sparked a curiosity in readers and nurtured a sense of  
706 intrinsic motivation to initiate further, deeper, learning of quantitative analyses. In so doing, we  
707 are hopeful that more researchers will join the second or third profile of researchers who seek to  
708 maintain or who are at the forefront, respectively, of understanding and applying emerging  
709 quantitative analyses.

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## Footnotes

<sup>1</sup> The 63 residual covariances represented three (i.e., past, present and future) method effects proposed by Prilleltensky et al. (2015). For example, allowing the residual term for each of the seven ‘present’ items to covary resulted in 21 residual covariances (and 21 multiplied by 3, the number of method effects, equals 63). The 70 covariances in the latent variable model resulted from 21 covariances between the scores derived from responses to the seven comparison instruments and 49 covariances between the scores derived from responses to the seven comparison instruments and the seven latent variables.

<sup>2</sup> Reference to specific page(s) and table(s) in Hancock and French (2013) was done with permission from Gregory R. Hancock (personal communication, September 16, 2016).

<sup>3</sup> Readers are referred to pp. 429-430 of the User’ Guide for an example.

<sup>4</sup> The 21 residual covariances between pairs of error terms for present items that were freely estimated in Myers, Park, et al. (2016) were fixed to zero. This reduced model fit the data as well as the more complex model,  $\Delta\chi_R^2(21) = 29, p = .106$ , and was consistent with related findings from previous research (Prilleltensky et al., 2015). Model-data fit indexes reported in Myers, Park, et al. were:  $\chi_R^2(119) = 175, p < .001$ , RMSEA = .027 (CI<sub>90%</sub> =.018-.035),  $p = .999$ , SRMR = .017, CFI = .99, and TLI = .98. Model-data fit indexes from the reduced model in this manuscript were:  $\chi_R^2(140) = 205, p < .001$ , RMSEA = .027 (CI<sub>90%</sub> =.018-.035),  $p = .999$ , SRMR = .018, CFI = .99, and TLI = .98.

<sup>5</sup> In several cases input statements provided were not necessary but such input was retained for pedagogical purposes. A complete treatment of syntax writing in *Mplus* is available in Muthén and Muthén (1998-2015).

<sup>6</sup>The owner(s) of the relevant real dataset had reservations about making their data publicly available. Consistent with some related methodological review papers (e.g., Myers, Brincks, et al., 2012) a simulated dataset that was nearly identical to the real dataset with regard to parameter estimates was created and provided as a compromise.

Table 1

*Overview of Usage of Exploratory Structural Equation Modelling in Sport and Exercise Psychology Research.*

Authors	Journal	Year	Study Objective	Rotation Method	Alternative Solutions Compared
Alcaraz, et al.	RQES	2015	Investigated how behavioral regulations mediated the relation between basic psychological needs and psychological well-being and ill-being in team-sport coaches; ESEM was used to test the factor structure of responses to each variable included in the model.	Not reported	ICM-CFA
Appleton, et al.	PSE	2016	Validated responses to coach-created Empowering and Disempowering Motivational Climate Questionnaire	Target rotation	Bi-factor ESEM; ICM-CFA
Chamarro, et al.	Psicothema	2015	Presented evidence of score validity for the Passion Scale in Spanish	Geomin rotation	None
Chiu, et al.	PR	2016	Explored the factor structure of scores of the shortened version of the Leadership Scale for Sport in a sample of collegiate swimmers	Geomin rotation	ICM-CFA
Fogarty, et al.	MPEES	2016	Examined the psychometric properties of scores from the Life Orientation Test-Revised, the Sport Confidence Inventory, and the Carolina SCI	Target rotation	ICM-CFA
Gucciardi, et al.	SEPP	2012	Reviewed mental toughness measurement issues and presented a psychometric examination of the most frequently used measure of mental toughness	Geomin rotation	ICM-CFA

Gunnell & Gaudreau	PID	2015	Tested the utility of the bi-factor model to examine motivation regarding physical activity and goal progress	Target rotation	Bi-factor ESEM
Hancox, et al.	IJSEP	2015	Explored the psychometric properties of scores from the Behavioral Regulation in Sport Questionnaire adapted to dance, as well as the tenability of different scoring protocols	Not reported	ICM-CFA
Kawabata & Mallett	JSS	2013	Re-assessed the factor structure of scores from the 24-item Sport Motivation Scale-6	Geomin rotation	ICM-CFA
Koh, et al.	IJSSC	2014	Assessed the factor structure of scores from the Coaching Behavior Scale for Sport for Singaporean youth athletes	Geomin rotation	ICM-CFA
Locke & Brawley	PSE	2016	Developed and demonstrated initial validity evidence for responses to the Exercise-related Cognitive Errors Questionnaire	Geomin rotation	None
Massey, et al.	PSE	2015	Provided validity evidence for responses to the Processes of Change in Psychological Skills Training Questionnaire	Not reported	ICM-CFA
Morin & Maïano	PSE	2011	Tested the psychometric properties of responses to the short form of the Physical Self-Inventory across French adolescents	Primarily geomin rotation; Several other rotations reported in the Appendix	ICM-CFA
Morin, et al.	PSE	2016	Examined the psychometric properties of scores on the English version of the short Physical Self-Inventory	Target rotation	ICM-CFA
Myers, et al.	SEPP	2014	Presented a general case for the possible utility of exploratory bi-factor analysis in sport and exercise psychology; tested	Target rotation; Considering other rotation criteria	ICM-CFA



Myers, et al.	JSEP	2011	the factor structure of responses to the Psychological Need Thwarting Scale Developed a revised version of the Coaching Efficacy Scale for Head Coaches of youth sport teams	Geomin rotation	ICM-CFA
Myers, et al.	JSEP	2012	Developed and provided initial validity evidence for measures derived from the Referee Self-Efficacy Scale	Target rotation	ICM-CFA
Myers	PSE	2013	Measured athletes' evaluations of their coach's competency within conceptual models of effective coaching	Geomin rotation; Target rotation	ICM-CFA
Nicholls, et al.	PSE	2016	Investigated a model, informed by self-regulation theories from health psychology research; ESEM was used to test the factor structure of responses to each variable included in the model.	Not reported	None
Payne, et al.	JSEP	2013	Developed and validated responses to a measure of impression motivation in team sport athletes	Geomin rotation	None
Perry, et al.	MPEES	2015	Investigated the appropriateness of using the ICM-CFA approach in sport and exercise psychology research	Geomin rotation	ICM-CFA
Rathwel & Young	MPEES	2016	Developed and validated scores from an adapted Youth Experience Scale for University Sport	Geomin rotation	ICM-CFA
Schellenberg, et al.	MPEES	2014	Examined the invariance of scores from the Passion Scale across groups of athletes, exercisers, and sports fans	Target rotation	ICM-CFA
Sparks, et al.	PSE	2016	Explored a higher-order measurement model comprising distinct relatedness-supportive teacher behaviours in physical education	Not reported	None
Stenling, et	FP	2015	Used bi-factor exploratory ESEM to	Target rotation	Bi-factor

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al.			examine the psychometric properties of responses to measures of coaches' need-supportive and controlling interpersonal styles.		ESEM; ICM-CFA
Tomás, et al.	JSEP	2014	Used ESEM as an alternative approach to evaluate the measurement invariance of scores from the Spanish version of the Physical Self-Description Questionnaire	Geomin rotation	ICM-CFA
Viladrich, et al.	IJSEP	2013	Examined the factorial validity of responses to the Behavioural Regulation Sport in Questionnaire when completed by young soccer players	Target rotation	ICM-CFA

---

*Note.* PSE = Psychology of Sport and Exercise; JSEP = Journal of Sport and Exercise Psychology; MPEES = Measurement in Physical Education and Exercise Science; IJSSC = International Journal of Sports Science & Coaching; JSMS = Journal of Science and Medicine in Sport; IJSEP = International Journal of Sport and Exercise Psychology; JSS = Journal of Sports Sciences; RQES = Research Quarterly for Exercise and Sport; SEPP = Sport, Exercise, and Performance Psychology; PSI = Psicothema; PR = Psychological Reports; FP = Frontiers in Psychology; PID = Personality and Individual Difference. None of the papers provided their syntax.

Table 2

*Overview of Usage of Mixture Modelling In Sport and Exercise Psychology Research.*

Authors	Journal/ Book	Year	Author Labelled Analysis	Syntax Available
Ivarsson, et al.	PSE	2015	Latent class analysis	No
Lindwall, et al.	PSE	2016	Latent profile analysis	No
Ullrich-French et al.	MPEES	2016	Latent profile analysis	No
Gerber, et al.	PSE	2014	Latent profile analysis	No
Wang, et al.	JSEP	2010	Structural equation mixture model (latent profile analysis combined with full SEM mixture model)	No
Wang et al.	PSE	2016	Latent profile analysis	No
Wang et al.	JSEP	2017	Latent profile analysis with auxiliary function	No
Martinet & Nicolas	SEPP	2016	Latent profile analysis, latent profile transition analysis	No
Martinet & Decret	JASP	2015	Latent profile analysis, latent profile transition analysis	No
Louvet, et al.	PSE	2009	Latent class growth modelling	No
Louvet, et al.	JSEP	2007	Latent class growth modelling	No
Morin & Wang	Book	2016	Latent profile analysis, mixture regression model, latent transition analysis, growth mixture model	Yes
Andruff, et al.	TQMP*	2009	Latent class growth modelling	Yes
Morin, et al.,	Child Dev*	2013	Growth mixture modelling	Yes
Morin et al.,	JID*	2015	Mixture structural equation modelling	Yes

*Note.* Select publications from prominent sport and exercise psychology journals. \* Example taken from related field to showcase syntax for mixture modelling. PSE = Psychology of Sport and Exercise; MPEES = Measurement in Physical Education and Exercise Science; JSEP = Journal of Sport and Exercise Psychology; JASP = Journal of Applied Sport Psychology; TQMP = Tutorials in Quantitative Methods for Psychology; Child Dev = Child Development; JID = Journal of Individual Differences.

Table 3

*Overview of the Similarities and Differences Between Frequentist and Bayesian Statistics (Reproduced with permission from van de Schoot et al., 2014).*

	Frequentist Statistics	Bayesian Statistics
Definition of the $p$ value	The probability of observing the same or more extreme data assuming that the null hypothesis is true in the population	The probability of the (null) hypothesis
Large samples needed?	Usually, when normal theory-based methods are used	Not necessarily
Inclusion of prior knowledge possible?	No	Yes
Nature of the parameters in the model	Unknown but fixed	Unknown and therefore random
Population parameter	One true value	A distribution of values reflecting uncertainty
Uncertainty is defined by	The sampling distribution based on the idea of infinite repeated sampling	Probability distribution for the population parameter
Estimated intervals	Confidence interval: over an infinity of samples taken from the population, 95% of these contain the true population value	Credibility interval: a 95% probability that the population value is within the limits of the interval

*Note.* With recent advancements in statistics and statistical software, there are cases in which prior knowledge can be incorporated as part of frequentist statistics such as using target rotation in exploratory structural equation modelling (e.g., Myers, Ahn, & Jin, 2013) and confirmatory mixture models (e.g., Finch & Bronk, 2011).

Table 4

*Overview of Usage of Bayesian Statistics in Sport and Exercise Psychology Research.*

Authors	Journal	Year	Use of Bayesian	Analysis	Type of Prior	Syntax Available
Barnett et al.	PSE	2012	Estimation	Dynamic linear model	Combination of non-informative and weakly informative	No
Constantinou et al.	PSE	2014	Probabilistic graphical model	Network analysis	Weakly informative	No
Doron & Gaudreau	JSEP	2014	Estimation	Multilevel modelling	Non-informative	No
Jackson et al.	JSEP	2014	Estimation	Factor analysis	Informative	No
Mahoney et al.	JSEP	2014	Estimation	Path analysis	Combination of weakly informative and informative	No
Chan et al.	JSEP	2015	Estimation	Structural equation modelling	Weakly informative	No
				Invariance analysis		
Gucciardi & Jackson	JSAMS	2015	Estimation	Structural equation modelling	Combination of weakly informative and informative	No*
Hodge & Gucciardi	JSEP	2015	Estimation	Path analysis	Combination of weakly informative and informative	No*
Stenling et al.	JSEP	2015	Estimation	Factor analysis	Combination of non-informative and weakly informative	No
Barnett et al.	PSE	2016	Estimation	Factor analysis	Comparison of non-informative and informative	No
Gucciardi, Peeling et al.	JSAMS	2016	Estimation	Structural equation modelling	Informative	Yes
Gucciardi, Zhang et al.	JSEP	2016	Estimation	Factor analysis	Combination of non-informative and weakly informative	Yes
				Invariance analysis		
Howle et al.	PSE	2016	Estimation	Factor analysis	Informative	No

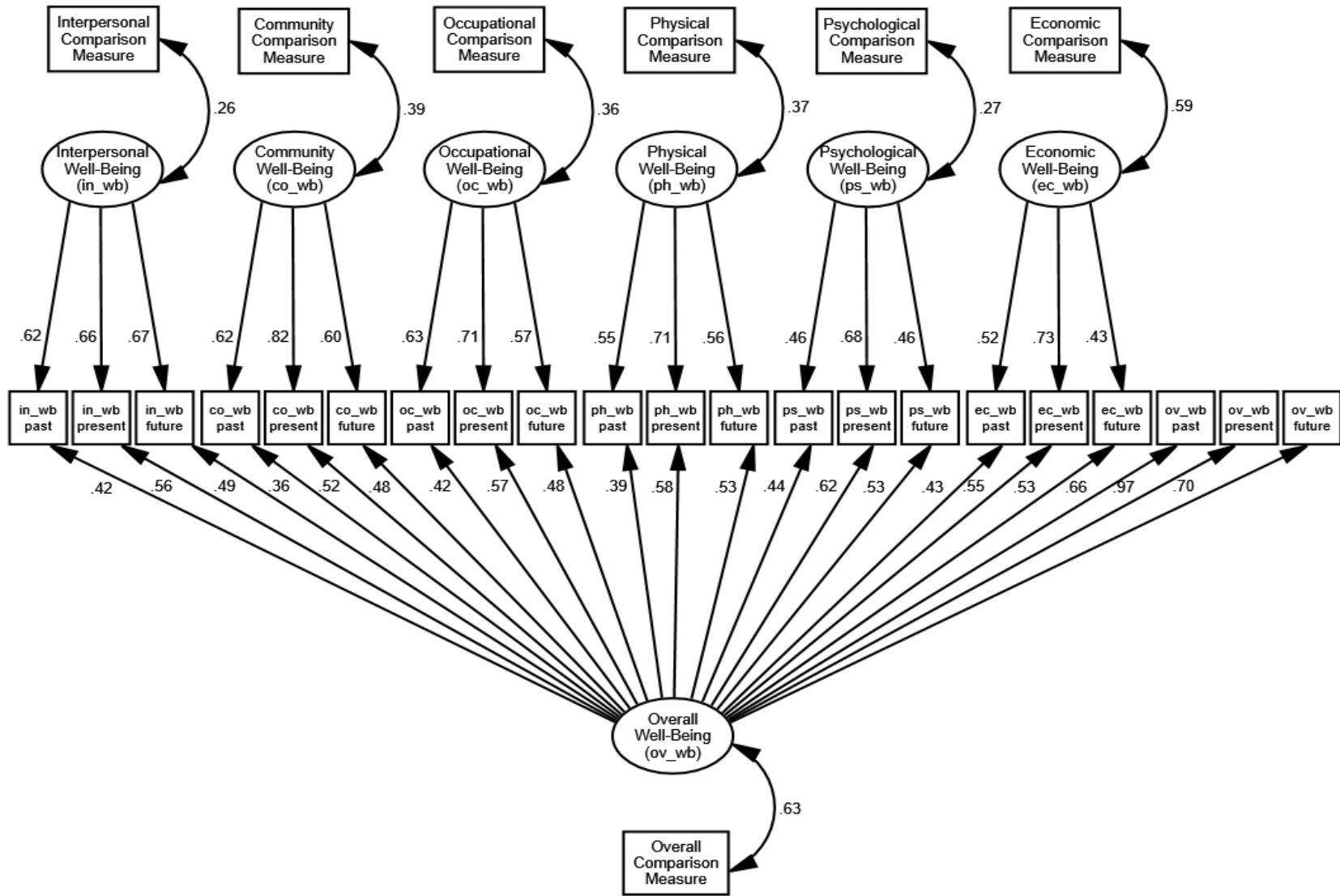
Niven & Markland	PSE	2016	Estimation	Path analysis Factor analysis	Comparison of non-informative and informative	Yes
Noordstar et al.	PSE	2016	Estimation	Factor analysis Invariance analysis Latent growth models	No information reported	No
Tamminen et al.	JSEP	2016	Estimation	Multilevel structural equation modelling	Non-informative	Yes

*Note.* PSE = Psychology of Sport and Exercise; JSEP = Journal of Sport and Exercise Psychology; JSAMS = Journal of Science and

Medicine in Sport. \* = authors indicated that interested readers can contact them for a copy of the syntax.

## Figure Captions (as a list)

*Figure 1.* Standardized parameter estimates commonly of primary interest (i.e., 39 pattern coefficients and 7 correlation coefficients) from Myers, Park, et al. (2016). Model parameters (e.g., variances; cross-loadings etc.) and identification constraints sometimes were omitted to reduce clutter.





## Appendix A

### Brief Demonstration 3: Software

**Monte Carlo Methods: Step 1.** Input for a real data analysis based on the Myers, Park, et al. (2016) example. Input file was written by the lead author of this manuscript in *Mplus* 7.4 based on Example 12.7 in Muthén and Muthén (1998-2015). Annotations are in italics and denoted with a ! symbol.

```
TITLE: Demonstration 3, Step 1
! Provided a title for the analysis: Demonstration 3.

DATA: FILE = dem_3.dat;
! Specified the name of the data file: dem_3.dat.

VARIABLE:
NAMES =over_pr over_pa over_fu
      inter_pr inter_pa inter_fu
      comm_pr comm_pa comm_fu
      occup_pr occup_pa occup_fu
      physi_pr physi_pa physi_fu
      psycho_pr psycho_pa psycho_fu
      econo_pr econo_pa econo_fu
      ex_over_wb ex_int_a ex_comm
      ex_occup ex_physical ex_psych
      ex_econo;
! The columns (i.e., variables) in the data file are in the given order.

      MISSING ARE ALL (-9999);
! For all variables a value of -9999 indicates a missing value.

ANALYSIS:
      ITERATIONS=10000;
! Maximum number of iterations.

      ESTIMATOR=MLR;
! Maximum likelihood parameter estimates with a chi-square test statistic
! and standard errors that are robust to conditional non-normality.

      ROTATION = Target(orthogonal);
! Orthogonal Target rotation.

MODEL:
      Ov BY over_pr-econo_fu(*t);
! ...BY: provided name for latent variable.
! BY: "measured by".
! BY...: identified indicator variables, in this case over_pr through
! econo_fu, for identified latent variable.
! (*t): defines a set of factors.

      In BY over_pr-econo_fu
```

```

over_pr~0 over_pa~0 over_fu~0
inter_pr~1.25 inter_pa~1.25 inter_fu~1.25
comm_pr~0 comm_pa~0 comm_fu~0
occup_pr~0 occup_pa~0 occup_fu~0
physi_pr~0 physi_pa~0 physi_fu~0
psycho_pr~0 psycho_pa~0 psycho_fu~0
econo_pr~0 econo_pa~0 econo_fu~0(*t);
! ~value: targeted value.

Co BY over_pr-econo_fu
over_pr~0 over_pa~0 over_fu~0
inter_pr~0 inter_pa~0 inter_fu~0
comm_pr~1.25 comm_pa~1.25 comm_fu~1.25
occup_pr~0 occup_pa~0 occup_fu~0
physi_pr~0 physi_pa~0 physi_fu~0
psycho_pr~0 psycho_pa~0 psycho_fu~0
econo_pr~0 econo_pa~0 econo_fu~0(*t);

Oc BY over_pr-econo_fu
over_pr~0 over_pa~0 over_fu~0
inter_pr~0 inter_pa~0 inter_fu~0
comm_pr~0 comm_pa~0 comm_fu~0
occup_pr~1.25 occup_pa~1.25 occup_fu~1.25
physi_pr~0 physi_pa~0 physi_fu~0
psycho_pr~0 psycho_pa~0 psycho_fu~0
econo_pr~0 econo_pa~0 econo_fu~0(*t);

Ph BY over_pr-econo_fu
over_pr~0 over_pa~0 over_fu~0
inter_pr~0 inter_pa~0 inter_fu~0
comm_pr~0 comm_pa~0 comm_fu~0
occup_pr~0 occup_pa~0 occup_fu~0
physi_pr~1.25 physi_pa~1.25 physi_fu~1.25
psycho_pr~0 psycho_pa~0 psycho_fu~0
econo_pr~0 econo_pa~0 econo_fu~0(*t);

Ps BY over_pr-econo_fu
over_pr~0 over_pa~0 over_fu~0
inter_pr~0 inter_pa~0 inter_fu~0
comm_pr~0 comm_pa~0 comm_fu~0
occup_pr~0 occup_pa~0 occup_fu~0
physi_pr~0 physi_pa~0 physi_fu~0
psycho_pr~1.25 psycho_pa~1.25 psycho_fu~1.25
econo_pr~0 econo_pa~0 econo_fu~0(*t);

Ec BY over_pr-econo_fu
over_pr~0 over_pa~0 over_fu~0
inter_pr~0 inter_pa~0 inter_fu~0
comm_pr~0 comm_pa~0 comm_fu~0
occup_pr~0 occup_pa~0 occup_fu~0
physi_pr~0 physi_pa~0 physi_fu~0
psycho_pr~0 psycho_pa~0 psycho_fu~0
econo_pr~1.25 econo_pa~1.25 econo_fu~1.25(*t);

Ov with ex_over_wb;
Ov with ex_int_a;
Ov with ex_comm;

```

```
Ov with ex_occup;  
Ov with ex_physical;  
Ov with ex_psych;  
Ov with ex_econo;  
! with: "co-varies" with; covariance between pairs of variables.
```

```
In with ex_over_wb;  
In with ex_int_a;  
In with ex_comm;  
In with ex_occup;  
In with ex_physical;  
In with ex_psych;  
In with ex_econo;
```

```
Co with ex_over_wb;  
Co with ex_int_a;  
Co with ex_comm;  
Co with ex_occup;  
Co with ex_physical;  
Co with ex_psych;  
Co with ex_econo;
```

```
Oc with ex_over_wb;  
Oc with ex_int_a;  
Oc with ex_comm;  
Oc with ex_occup;  
Oc with ex_physical;  
Oc with ex_psych;  
Oc with ex_econo;
```

```
Ph with ex_over_wb;  
Ph with ex_int_a;  
Ph with ex_comm;  
Ph with ex_occup;  
Ph with ex_physical;  
Ph with ex_psych;  
Ph with ex_econo;
```

```
Ps with ex_over_wb;  
Ps with ex_int_a;  
Ps with ex_comm;  
Ps with ex_occup;  
Ps with ex_physical;  
Ps with ex_psych;  
Ps with ex_econo;
```

```
Ec with ex_over_wb;  
Ec with ex_int_a;  
Ec with ex_comm;  
Ec with ex_occup;  
Ec with ex_physical;  
Ec with ex_psych;  
Ec with ex_econo;
```

```
ex_over_wb with ex_int_a;  
ex_over_wb with ex_comm;  
ex_over_wb with ex_occup;
```

ex\_over\_wb with ex\_physical;  
ex\_over\_wb with ex\_psych;  
ex\_over\_wb with ex\_econo;

ex\_int\_a with ex\_comm;  
ex\_int\_a with ex\_occup;  
ex\_int\_a with ex\_physical;  
ex\_int\_a with ex\_psych;  
ex\_int\_a with ex\_econo;

ex\_comm with ex\_occup;  
ex\_comm with ex\_physical;  
ex\_comm with ex\_psych;  
ex\_comm with ex\_econo;

ex\_occup with ex\_physical;  
ex\_occup with ex\_psych;  
ex\_occup with ex\_econo;

ex\_physical with ex\_psych;  
ex\_physical with ex\_econo;

ex\_psych with ex\_econo;

over\_pa with inter\_pa;  
over\_pa with comm\_pa;  
over\_pa with occup\_pa;  
over\_pa with physi\_pa;  
over\_pa with psycho\_pa;  
over\_pa with econo\_pa;

inter\_pa with comm\_pa;  
inter\_pa with occup\_pa;  
inter\_pa with physi\_pa;  
inter\_pa with psycho\_pa;  
inter\_pa with econo\_pa;

comm\_pa with occup\_pa;  
comm\_pa with physi\_pa;  
comm\_pa with psycho\_pa;  
comm\_pa with econo\_pa;

occup\_pa with physi\_pa;  
occup\_pa with psycho\_pa;  
occup\_pa with econo\_pa;

physi\_pa with psycho\_pa;  
physi\_pa with econo\_pa;

psycho\_pa with econo\_pa;

over\_fu with inter\_fu;  
over\_fu with comm\_fu;  
over\_fu with occup\_fu;  
over\_fu with physi\_fu;  
over\_fu with psycho\_fu;  
over\_fu with econo\_fu;

```
inter_fu with comm_fu;  
inter_fu with occup_fu;  
inter_fu with physi_fu;  
inter_fu with psycho_fu;  
inter_fu with econo_fu;
```

```
comm_fu with occup_fu;  
comm_fu with physi_fu;  
comm_fu with psycho_fu;  
comm_fu with econo_fu;
```

```
occup_fu with physi_fu;  
occup_fu with psycho_fu;  
occup_fu with econo_fu;
```

```
physi_fu with psycho_fu;  
physi_fu with econo_fu;
```

```
psycho_fu with econo_fu;
```

OUTPUT: SAMPSTAT STANDARDIZED tech1;

*! SAMPSTAT: requested sample statistics for data being analyzed.*

*! STAND: requested standardized parameter estimates and their standard*

*! errors.*

*! tech1: requested arrays containing parameter specifications and starting*

*! values for all freely estimated parameters in the model*

SAVEDATA: ESTIMATES = final model estimates.dat;

*! Specified the name of the file, final model estimates, in which parameter*

*! estimates will be saved.*

## Appendix B

### Brief Demonstration 3: Software

**Monte Carlo Methods: Step 2.** Input for a Monte Carlo simulation study where parameter estimates saved from Step 1 (see Appendix B) are used for population parameter values for data generation (i.e., replications) and coverage. Input file was written by the lead author of this manuscript in *Mplus* 7.4 based on Example 12.8 in Muthén and Muthén (1998-2015). Annotations are provided for commands not explained in Appendix B and are in italics and denoted with a ! symbol.

TITLE: Demonstration 3, Step 2

MONTECARLO:

*! A Monte Carlo study ensues.*

```

    NAMES = over_pr over_pa over_fu
           inter_pr inter_pa inter_fu
           comm_pr comm_pa comm_fu
           occup_pr occup_pa occup_fu
           physi_pr physi_pa physi_fu
           psycho_pr psycho_pa psycho_fu
           econo_pr econo_pa econo_fu
           ex_over_wb ex_int_a ex_comm
           ex_occup ex_physical ex_psych
           ex_econo;

```

```

    NOBSERVATIONS = 1000;

```

*! Desired sample size for each replication.*

*! Only this line of code needs to be changed (i.e., NOBSERVATIONS = 500 or  
! NOBSERVATIONS = 250) to reproduce the other two results.*

```

    NREPS = 10000;

```

*! Number of replications to be drawn.*

```

    SEED = 82872;

```

*! Provides a starting place for the random draws.*

```

    POPULATION = final model estimates.dat;

```

*! Names the data set that contains population parameter values.*

```

    COVERAGE = final model estimates.dat;

```

*! Names the data set that contains population parameter values.*

ANALYSIS:

```

    ESTIMATOR=MLR;

```

```

    ROTATION = Target(orthogonal);

```

MODEL POPULATION:

*! Provides the population model.*

Ov BY over\_pr-econo\_fu;  
In BY over\_pr-econo\_fu;  
Co BY over\_pr-econo\_fu;  
Oc BY over\_pr-econo\_fu;  
Ph BY over\_pr-econo\_fu;  
Ps BY over\_pr-econo\_fu;  
Ec BY over\_pr-econo\_fu;

Ov with ex\_over\_wb;  
Ov with ex\_int\_a;  
Ov with ex\_comm;  
Ov with ex\_occup;  
Ov with ex\_physical;  
Ov with ex\_psych;  
Ov with ex\_econo;

In with ex\_over\_wb;  
In with ex\_int\_a;  
In with ex\_comm;  
In with ex\_occup;  
In with ex\_physical;  
In with ex\_psych;  
In with ex\_econo;

Co with ex\_over\_wb;  
Co with ex\_int\_a;  
Co with ex\_comm;  
Co with ex\_occup;  
Co with ex\_physical;  
Co with ex\_psych;  
Co with ex\_econo;

Oc with ex\_over\_wb;  
Oc with ex\_int\_a;  
Oc with ex\_comm;  
Oc with ex\_occup;  
Oc with ex\_physical;  
Oc with ex\_psych;  
Oc with ex\_econo;

Ph with ex\_over\_wb;  
Ph with ex\_int\_a;  
Ph with ex\_comm;  
Ph with ex\_occup;  
Ph with ex\_physical;  
Ph with ex\_psych;  
Ph with ex\_econo;

Ps with ex\_over\_wb;  
Ps with ex\_int\_a;  
Ps with ex\_comm;  
Ps with ex\_occup;  
Ps with ex\_physical;  
Ps with ex\_psych;  
Ps with ex\_econo;

Ec with ex\_over\_wb;  
Ec with ex\_int\_a;  
Ec with ex\_comm;  
Ec with ex\_occup;  
Ec with ex\_physical;  
Ec with ex\_psych;  
Ec with ex\_econo;

ex\_over\_wb with ex\_int\_a;  
ex\_over\_wb with ex\_comm;  
ex\_over\_wb with ex\_occup;  
ex\_over\_wb with ex\_physical;  
ex\_over\_wb with ex\_psych;  
ex\_over\_wb with ex\_econo;

ex\_int\_a with ex\_comm;  
ex\_int\_a with ex\_occup;  
ex\_int\_a with ex\_physical;  
ex\_int\_a with ex\_psych;  
ex\_int\_a with ex\_econo;

ex\_comm with ex\_occup;  
ex\_comm with ex\_physical;  
ex\_comm with ex\_psych;  
ex\_comm with ex\_econo;

ex\_occup with ex\_physical;  
ex\_occup with ex\_psych;  
ex\_occup with ex\_econo;

ex\_physical with ex\_psych;  
ex\_physical with ex\_econo;

ex\_psych with ex\_econo;

over\_pa with inter\_pa;  
over\_pa with comm\_pa;  
over\_pa with occup\_pa;  
over\_pa with physi\_pa;  
over\_pa with psycho\_pa;  
over\_pa with econo\_pa;

inter\_pa with comm\_pa;  
inter\_pa with occup\_pa;  
inter\_pa with physi\_pa;  
inter\_pa with psycho\_pa;  
inter\_pa with econo\_pa;

comm\_pa with occup\_pa;  
comm\_pa with physi\_pa;  
comm\_pa with psycho\_pa;  
comm\_pa with econo\_pa;

occup\_pa with physi\_pa;  
occup\_pa with psycho\_pa;  
occup\_pa with econo\_pa;



```

physi_pa with psycho_pa;
physi_pa with econo_pa;

psycho_pa with econo_pa;

over_fu with inter_fu;
over_fu with comm_fu;
over_fu with occup_fu;
over_fu with physi_fu;
over_fu with psycho_fu;
over_fu with econo_fu;

inter_fu with comm_fu;
inter_fu with occup_fu;
inter_fu with physi_fu;
inter_fu with psycho_fu;
inter_fu with econo_fu;

comm_fu with occup_fu;
comm_fu with physi_fu;
comm_fu with psycho_fu;
comm_fu with econo_fu;

occup_fu with physi_fu;
occup_fu with psycho_fu;
occup_fu with econo_fu;

physi_fu with psycho_fu;
physi_fu with econo_fu;

psycho_fu with econo_fu;

```

## MODEL:

*! Provides the model to be fit to each replication that is generated.*

```

Ov BY over_pr-econo_fu(*t);

In BY over_pr-econo_fu
over_pr~0 over_pa~0 over_fu~0
inter_pr~1.25 inter_pa~1.25 inter_fu~1.25
comm_pr~0 comm_pa~0 comm_fu~0
occup_pr~0 occup_pa~0 occup_fu~0
physi_pr~0 physi_pa~0 physi_fu~0
psycho_pr~0 psycho_pa~0 psycho_fu~0
econo_pr~0 econo_pa~0 econo_fu~0(*t);

Co BY over_pr-econo_fu
over_pr~0 over_pa~0 over_fu~0
inter_pr~0 inter_pa~0 inter_fu~0
comm_pr~1.25 comm_pa~1.25 comm_fu~1.25
occup_pr~0 occup_pa~0 occup_fu~0
physi_pr~0 physi_pa~0 physi_fu~0
psycho_pr~0 psycho_pa~0 psycho_fu~0
econo_pr~0 econo_pa~0 econo_fu~0(*t);

```

```

Oc BY over_pr-econo_fu
over_pr~0 over_pa~0 over_fu~0
inter_pr~0 inter_pa~0 inter_fu~0
comm_pr~0 comm_pa~0 comm_fu~0
occup_pr~1.25 occup_pa~1.25 occup_fu~1.25
physi_pr~0 physi_pa~0 physi_fu~0
psycho_pr~0 psycho_pa~0 psycho_fu~0
econo_pr~0 econo_pa~0 econo_fu~0(*t);

Ph BY over_pr-econo_fu
over_pr~0 over_pa~0 over_fu~0
inter_pr~0 inter_pa~0 inter_fu~0
comm_pr~0 comm_pa~0 comm_fu~0
occup_pr~0 occup_pa~0 occup_fu~0
physi_pr~1.25 physi_pa~1.25 physi_fu~1.25
psycho_pr~0 psycho_pa~0 psycho_fu~0
econo_pr~0 econo_pa~0 econo_fu~0(*t);

Ps BY over_pr-econo_fu
over_pr~0 over_pa~0 over_fu~0
inter_pr~0 inter_pa~0 inter_fu~0
comm_pr~0 comm_pa~0 comm_fu~0
occup_pr~0 occup_pa~0 occup_fu~0
physi_pr~0 physi_pa~0 physi_fu~0
psycho_pr~1.25 psycho_pa~1.25 psycho_fu~1.25
econo_pr~0 econo_pa~0 econo_fu~0(*t);

Ec BY over_pr-econo_fu
over_pr~0 over_pa~0 over_fu~0
inter_pr~0 inter_pa~0 inter_fu~0
comm_pr~0 comm_pa~0 comm_fu~0
occup_pr~0 occup_pa~0 occup_fu~0
physi_pr~0 physi_pa~0 physi_fu~0
psycho_pr~0 psycho_pa~0 psycho_fu~0
econo_pr~1.25 econo_pa~1.25 econo_fu~1.25(*t);

Ov with ex_over_wb;
Ov with ex_int_a;
Ov with ex_comm;
Ov with ex_occup;
Ov with ex_physical;
Ov with ex_psyche;
Ov with ex_econo;

In with ex_over_wb;
In with ex_int_a;
In with ex_comm;
In with ex_occup;
In with ex_physical;
In with ex_psyche;
In with ex_econo;

Co with ex_over_wb;
Co with ex_int_a;
Co with ex_comm;
Co with ex_occup;
Co with ex_physical;

```

Co with ex\_psych;  
Co with ex\_econo;

Oc with ex\_over\_wb;  
Oc with ex\_int\_a;  
Oc with ex\_comm;  
Oc with ex\_occup;  
Oc with ex\_physical;  
Oc with ex\_psych;  
Oc with ex\_econo;

Ph with ex\_over\_wb;  
Ph with ex\_int\_a;  
Ph with ex\_comm;  
Ph with ex\_occup;  
Ph with ex\_physical;  
Ph with ex\_psych;  
Ph with ex\_econo;

Ps with ex\_over\_wb;  
Ps with ex\_int\_a;  
Ps with ex\_comm;  
Ps with ex\_occup;  
Ps with ex\_physical;  
Ps with ex\_psych;  
Ps with ex\_econo;

Ec with ex\_over\_wb;  
Ec with ex\_int\_a;  
Ec with ex\_comm;  
Ec with ex\_occup;  
Ec with ex\_physical;  
Ec with ex\_psych;  
Ec with ex\_econo;

ex\_over\_wb with ex\_int\_a;  
ex\_over\_wb with ex\_comm;  
ex\_over\_wb with ex\_occup;  
ex\_over\_wb with ex\_physical;  
ex\_over\_wb with ex\_psych;  
ex\_over\_wb with ex\_econo;

ex\_int\_a with ex\_comm;  
ex\_int\_a with ex\_occup;  
ex\_int\_a with ex\_physical;  
ex\_int\_a with ex\_psych;  
ex\_int\_a with ex\_econo;

ex\_comm with ex\_occup;  
ex\_comm with ex\_physical;  
ex\_comm with ex\_psych;  
ex\_comm with ex\_econo;

ex\_occup with ex\_physical;  
ex\_occup with ex\_psych;  
ex\_occup with ex\_econo;

ex\_physical with ex\_psych;  
ex\_physical with ex\_econo;

ex\_psych with ex\_econo;

over\_pa with inter\_pa;  
over\_pa with comm\_pa;  
over\_pa with occup\_pa;  
over\_pa with physi\_pa;  
over\_pa with psycho\_pa;  
over\_pa with econo\_pa;

inter\_pa with comm\_pa;  
inter\_pa with occup\_pa;  
inter\_pa with physi\_pa;  
inter\_pa with psycho\_pa;  
inter\_pa with econo\_pa;

comm\_pa with occup\_pa;  
comm\_pa with physi\_pa;  
comm\_pa with psycho\_pa;  
comm\_pa with econo\_pa;

occup\_pa with physi\_pa;  
occup\_pa with psycho\_pa;  
occup\_pa with econo\_pa;

physi\_pa with psycho\_pa;  
physi\_pa with econo\_pa;

psycho\_pa with econo\_pa;

over\_fu with inter\_fu;  
over\_fu with comm\_fu;  
over\_fu with occup\_fu;  
over\_fu with physi\_fu;  
over\_fu with psycho\_fu;  
over\_fu with econo\_fu;

inter\_fu with comm\_fu;  
inter\_fu with occup\_fu;  
inter\_fu with physi\_fu;  
inter\_fu with psycho\_fu;  
inter\_fu with econo\_fu;

comm\_fu with occup\_fu;  
comm\_fu with physi\_fu;  
comm\_fu with psycho\_fu;  
comm\_fu with econo\_fu;

occup\_fu with physi\_fu;  
occup\_fu with psycho\_fu;  
occup\_fu with econo\_fu;

physi\_fu with psycho\_fu;  
physi\_fu with econo\_fu;

```
psycho_fu with econo_fu;
```

```
OUTPUT:      tech1 tech9;
```

```
! tech9: Print error messages related to convergence for each replication.
```

## Appendix C

## Brief Demonstration 3: Software

**Monte Carlo Methods: Step 2.** Truncated output identifying the power estimation value for each focal parameter when sample size equalled 250. The right-most column labelled, % Sig Coeff, provides power estimation values.

## MODEL RESULTS

		ESTIMATES			S. E.	M. S. E.	95% Cover	% Sig Coeff
		Population	Average	Std. Dev.	Average			
OV	BY							
	OVER_PR	1.987	1.9532	0.2478	0.1390	0.0625	0.931	0.998
	OVER_PA	1.427	1.4010	0.1772	0.1326	0.0321	0.927	0.999
	OVER_FU	1.458	1.4324	0.1723	0.1237	0.0303	0.930	0.999
IN	BY							
	INTER_PR	1.456	1.4476	0.0944	0.0955	0.0090	0.947	1.000
	INTER_PA	1.325	1.3187	0.1063	0.1051	0.0113	0.943	1.000
	INTER_FU	1.346	1.3414	0.0925	0.0916	0.0086	0.944	1.000
CO	BY							
	COMM_PR	1.688	1.6772	0.0857	0.0851	0.0075	0.939	1.000
	COMM_PA	1.377	1.3722	0.1106	0.1092	0.0123	0.944	1.000
	COMM_FU	1.226	1.2227	0.0909	0.0913	0.0083	0.948	1.000
OC	BY							
	OCCUP_PR	1.930	1.9202	0.1128	0.1135	0.0128	0.947	1.000
	OCCUP_PA	1.653	1.6463	0.1289	0.1283	0.0167	0.947	1.000
	OCCUP_FU	1.382	1.3797	0.1075	0.1089	0.0116	0.950	1.000
PH	BY							
	PHYSI_PR	1.472	1.4620	0.0918	0.0904	0.0085	0.940	1.000
	PHYSI_PA	1.229	1.2252	0.1168	0.1172	0.0137	0.948	1.000
	PHYSI_FU	1.107	1.1050	0.0937	0.0929	0.0088	0.946	1.000
PS	BY							
	PSYCHO_PR	1.508	1.4993	0.1089	0.1135	0.0119	0.951	1.000

EMERGENT QUANTITATIVE ANALYSES

PSYCHO_PA	1.018	1.0153	0.1198	0.1232	0.0144	0.950	1.000
PSYCHO_FU	0.952	0.9500	0.0971	0.0996	0.0094	0.951	1.000
EC BY							
ECONO_PR	1.833	1.8155	0.1086	0.1062	0.0121	0.936	1.000
ECONO_PA	1.249	1.2458	0.1253	0.1275	0.0157	0.948	1.000
ECONO_FU	0.981	0.9839	0.1072	0.1064	0.0115	0.946	1.000
OV WITH							
EX_OVER_WB	4.757	4.7067	0.4399	0.4244	0.1960	0.936	0.999
IN WITH							
EX_INT_A	4.609	4.5880	1.0991	1.1062	1.2083	0.951	0.986
CO WITH							
EX_COMM	0.402	0.3967	0.0573	0.0568	0.0033	0.945	1.000
OC WITH							
EX_OCCUP	2.679	2.6537	0.4307	0.4331	0.1861	0.946	1.000
PH WITH							
EX_PHYSICA	3.811	3.7911	0.6919	0.6815	0.4791	0.945	1.000
PS WITH							
EX_PSYCH	2.527	2.4959	0.5475	0.5488	0.3007	0.947	0.994
EC WITH							
EX_ECONO	1.340	1.3306	0.1164	0.1179	0.0136	0.948	1.000

## Appendix D

### Brief Demonstration 3: Software

**Monte Carlo Methods: Step 1.** Readers can download the file named dem\_3.dat (available on the online supplemental materials) and try running the syntax provided in Appendix A and Appendix B themselves. Changing the NREPS command from NREPS=10000 to NREPS=1000 should significantly reduce computational time (and should be sufficient for demonstration purposes) with only minor changes in the results.