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Bifactor exploratory structural equation modeling: A meta-analytic review of model fit

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Multivariate behavioral research often focuses on latent constructs—such as motivation, self-concept, or wellbeing—that cannot be directly observed. Typically, these latent constructs are measured with items in standardized instruments. To test the factorial structure and multidimensionality of latent constructs in educational and psychological research, Morin et al. (2016a) proposed bifactor exploratory structural equation modeling (B-ESEM). This meta-analytic review (158 studies, $k = 308$, $N = 778,624$) aimed to estimate the extent to which B-ESEM model fit differs from other model representations, including confirmatory factor analysis (CFA), exploratory structural equation modeling (ESEM), hierarchical CFA, hierarchical ESEM, and bifactor-CFA. The study domains included learning and instruction, motivation and emotion, self and identity, depression and wellbeing, and interpersonal relations. The meta-analyzed fit indices were the χ^2/df ratio, the comparative fit index (CFI), the Tucker-Lewis index (TLI), the root mean square error of approximation (RMSEA), and the standardized root mean squared residual (SRMR). The findings of this meta-analytic review indicate that the B-ESEM model fit is superior to the fit of reference models. Furthermore, the results suggest that model fit is sensitive to sample size, item number, and the number of specific and general factors in a model.

KEYWORDS

factor analysis, meta-analysis, multidimensionality, goodness-of-fit, exploratory structural equation modeling, bifactor ESEM

Introduction

To examine the factorial structure and multidimensionality of latent constructs in educational and psychological research, Morin et al. (2016a) proposed bifactor exploratory structural equation modeling (B-ESEM) as a methodological synergy that integrates bifactor modeling and exploratory structural equation modeling. Since their seminal paper, a number of studies have applied B-ESEM in research on learning and instruction, motivation and emotion, self and identity, wellbeing, and other areas. The present systematic review and meta-analysis aimed to collect and describe these studies, meta-analyze their reported model fit, and estimate the extent to which the fit of the B-ESEM model differs from that of the other tested model representations. A secondary aim was to analyze how sensitive model fit was to sample size,

item number, and the number of specific and general factors in a model.

Exploring the factor structure of multidimensional constructs

Researchers interested in exploring the factorial structure of a multidimensional construct can choose among analytical options including confirmatory factor analysis (CFA; Jöreskog, 1969), exploratory structural equation modeling (ESEM; Asparouhov and Muthén, 2009), and hierarchical and bifactor representations of CFA and ESEM (Rindskopf and Rose, 1988; Reise, 2012; Morin et al., 2013, 2016a). A number of excellent review papers and pedagogical illustrations of these factor analytic techniques exist (Marsh, 2007; Marsh et al., 2009, 2014; Reise, 2012; Morin et al., 2013, 2016a, 2020; Bandalos and Finney, 2018; Sellbom and Tellegen, 2019). Interested readers can consult these excellent resources for more detail, but let us briefly review how the factor structure of multidimensional latent constructs can be represented and analyzed. Figure 1 offers an overview of schematic model representations.

The simplest form of representation and analysis, arguably, is a one-factor first-order model in which all items are loaded on a single factor. More complex are CFA and ESEM that can be applied to test a hypothesized factor structure: in CFA, items load on a single factor with zero cross-loadings; in ESEM, too, items load a single factor but without CFA's strict requirement of zero cross-loadings. When exploring hierarchically ordered constructs, CFA and ESEM can be extended to models in which items are loaded on specific lower-order factors (L-factors), which are in turn loaded on a single higher-order factor (the H-factor). Finally, in the case of bifactor modeling, CFA and ESEM can be extended to a model in which items are loaded on one general factor (the G-factor) representing a global overarching construct as well as on multiple specific factors (S-factors) representing their subscales—in bifactor CFA (B-CFA) without and in bifactor ESEM (B-ESEM) with free estimation of cross-loadings between items and non-target factors. B-ESEM in particular has been shown to result in a better model fit for a number of multidimensional hierarchical constructs that are frequently explored in educational and psychological research¹.

B-ESEM in multivariate behavioral research

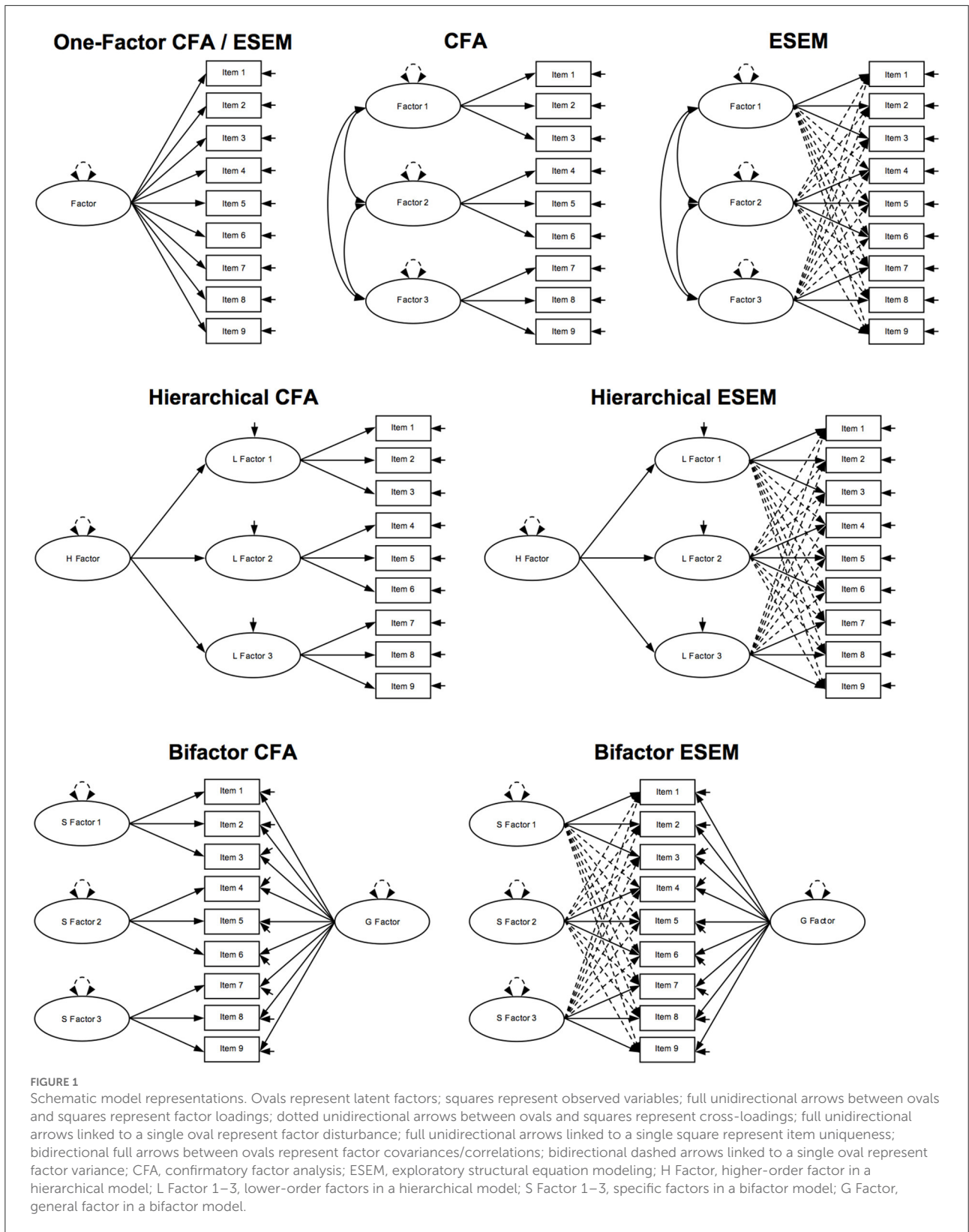
A growing number of studies test the multidimensionality of latent constructs in research on learning and instruction,

¹ For reasons of completeness, it is worth mentioning that researchers can also use Bayesian SEM (BSEM; Muthén and Asparouhov, 2012) and set-ESEM (Marsh et al., 2020).

motivation and emotion, self and identity, wellbeing and depression, and interpersonal relationships. In the domain of learning and instruction, for example, Scherer et al. (2016) identified the presence of a general factor of student-perceived instructional quality and three distinct sub-dimensions: teacher support, cognitive activation, and classroom management. Fernandez-Rio and colleagues explored the factor structure of a scale measuring dimensions of cooperative learning. In the domain of motivation and emotion, Howard et al. (2020) showed that motivation scales based on the self-determination theory were best represented as a B-ESEM model in which all items defined specific motivation regulatory qualities on a continuum (from amotivation to intrinsic motivation) and were also used to define a global self-determination factor. Perera et al. (2018b) tested the structure of teacher engagement, identifying a general factor and specific cognitive-physical, emotional, and social engagement factors. In the domain of self and identity, for example, Arens et al. (2021) explored the structure of academic self-concept and reported that a B-ESEM representation including one general self-concept factor and multiple specific self-concept factors (for German, English, math, physics, chemistry, biology, and history) provided the best model fit compared with reference models. In the domain of wellbeing and depression, Morin et al. (2017) tested the dimensionality of the Index of Psychological WellBeing at Work that can also be used to wellbeing of teachers. In the domain of interpersonal relations, Ratelle et al. (2018) showed that the factor structure of a scale measuring parental structure, including parents' rules, predictability, feedback, opportunities, rationale, and authority, was best represented as a B-ESEM model.

These individual studies support the assumption that B-ESEM is best used to deal with multidimensional hierarchical constructs, yet the extent to which model fit of B-ESEM differs from other model representations has not yet been investigated across studies, domains, and scales. A meta-analysis of published studies could help to close this research gap. Among the frequently used parameters used in the studies reviewed to test model fit are the χ^2/df ratio (Pearson, 1900), the comparative fit index (CFI; Bentler, 1990), the Tucker-Lewis index (TLI; Bentler and Bonett, 1990), the root mean square error of approximation (RMSEA; Steiger, 1990), and the standardized root mean squared residual (SRMR; Bentler, 1995). Table 1 provides an overview of goodness-of-fit indices used in B-ESEM studies². Furthermore, if the evidence that model fit indices are sensitive to sample size, item number, and factor number from simulation studies is valid (Hu and Bentler, 1999; Marsh et al., 2004; Shi et al., 2019), it would be interesting to replicate these

² Despite the widespread use of goodness-of-fit indices to evaluate model fit, many scholars warn against the use of fixed cutoff values (Marsh et al., 2004). McNeish and Wolf (2022) propose dynamic fit index cutoffs as an alternative.



findings through a research synthesis using real data rather than simulated data. Such a synthesis would also be useful to describe

the status quo of research adopting a B-ESEM framework, the mapping of tested constructs (such as academic self-concept;

TABLE 1 Factor analytic techniques and model fit indices.

	Abbreviation	References
Factor analytic techniques		
Confirmatory factor analysis	CFA	Jöreskog, 1969
Exploratory structural equation modeling	ESEM	Asparouhov and Muthén, 2009
Hierarchical confirmatory factor analysis	H-CFA	Rindskopf and Rose, 1988
Hierarchical exploratory structural equation modeling	H-ESEM	Morin et al., 2013
Bifactor confirmatory factor analysis	B-CFA	Reise, 2012
Bifactor exploratory structural equation modeling	B-ESEM	Morin et al., 2016a
Model fit indices		
Chi square/degrees of freedom ratio	χ^2/df	Pearson, 1900
Comparative fit index	CFI	Bentler, 1990
Tucker-Lewis index	TLI	Bentler and Bonett, 1990
Root mean square error of approximation	RMSEA	Steiger, 1990
Standardized root mean squared residual	SRMR	Bentler, 1995

Arens et al., 2021), scales (such as the Multidimensional Work Motivation Scale; Howard et al., 2020), and domains (such as learning and instruction).

The present study

Based on a systematic literature review and meta-analysis of previous research applying the B-ESEM framework, the present study compares goodness-of-fit indices of B-ESEM with reference models. The study sought to answer three research questions: (1) Which domains, constructs, and scales are targeted in studies adopting a B-ESEM framework? (2) What is the model fit of B-ESEM representations compared to CFA, ESEM, H-CFA, H-ESEM, and B-CFA representations? (3) How sensitive is model fit to sample size, item number, and the number of specific and general factors in a model?

Methods

Steps in conducting and reporting this meta-analytic review of B-ESEM included defining inclusion and exclusion criteria, searching the literature, coding information from the retrieved studies, calculating intercoder reliability, and meta-analyzing the fit indices (Page et al., 2021). The following sections describe these steps in more detail.

Defining inclusion and exclusion criteria

We identified studies that reported goodness-of-fit indices of B-ESEM in educational and psychological research. Table 2 presents the criteria for inclusion and exclusion of these studies.

To be included, a study had to report a χ^2 (df), CFI, TLI, RMSEA, or SRMR estimate of a bifactor ESEM model and compare it with a CFA, ESEM, H-CFA, H-ESEM, or B-CFA reference model. Studies were omitted if they did not examine a B-ESEM representation, did not compare B-ESEM to a reference model, or relied on simulated data. To minimize publication bias, our literature search was deliberately broad and included reports in journal articles, book chapters, monographs, conference papers, and unpublished theses or dissertations, regardless of participant population, publication language, publication year, or domain.

To illustrate how we applied the criteria, examples of both excluded and included articles may help. On the one hand, an excellent study by Zhu et al. (2020) that reports model fit evaluation of a B-ESEM representation of mindfulness was excluded because B-ESEM was not compared with other models; rather, the B-ESEM factor scores were used to perform latent profile analyses. On the other hand, a study by Arens et al. (2021) was included because the authors compared goodness-of-fit indices obtained from higher-order and bifactor ESEM representations of the structure of academic self-concept.

Searching the literature

Grounded in the inclusion criteria presented in Table 2, a two-phase literature search was performed. First, we conducted an electronic search of five databases—ERIC, PsycINFO, PubMed, Scopus, and Web of Science—for all publication types in any language published up to December 31, 2021 and with relevant keywords in the title or abstract. The keywords were *bifactor exploratory structural equation modeling*, *bifactor ESEM*, and *B-ESEM*, along with their spelling variants. This database search resulted in a total of 525 hits: 25 from ERIC,

TABLE 2 Criteria for inclusion and exclusion in the meta-analytic review.

Criterion	Inclusion	Exclusion
Model representation	B-ESEM	No B-ESEM
Reference model	CFA, ESEM, H-CFA, H-ESEM, or B-CFA	No reference model
Model fit index	χ^2 (<i>df</i>), CFI, TLI, RMSEA, or SRMR	No χ^2 (<i>df</i>), CFI, TLI, RMSEA, or SRMR
Data type	Original data	Simulated data
Study type	Original research	Method reviews, meta-analyses, errata, editorials
Publication type	All publication types, including journal articles, theses, monographs, chapters, conference proceedings	–
Publication language	All languages	–
Publication year	All years	–
Population	All populations	–
Domain	All domains	–

B-ESEM, bifactor exploratory structural equation modeling; CFA, confirmatory factor analysis; ESEM, exploratory structural equation modeling; H-CFA, hierarchical confirmatory factor analysis; H-ESEM, hierarchical exploratory structural equation modeling; B-CFA, bifactor confirmatory factor analysis; CFI, comparative fit index; TLI, Tucker-Lewis index, RMSEA, root mean square error of approximation, SRMR, standardized root mean squared residual.

106 from PsycINFO, 34 from PubMed, 182 from Scopus, and 178 from Web of Science. Two trained raters eliminated 318 duplicates because they were listed in more than one database, after which 207 articles remained. Next, both raters independently and in duplicate screened a random subset of the 207 identified articles (10 percent; $n = 21$ articles). As interrater agreement was high, with Cohen's $\kappa = 0.881$ (95% CI = 0.659–1.00), a single rater continued to screen the remaining studies for eligibility by reading titles and abstracts, after which 186 articles remained. Both raters then read the full texts of these articles independently to check for eligibility, and 60 studies were excluded because they did not examine a B-ESEM representation (37 removals) or did not compare B-ESEM to a reference model (23 removals), resulting in 126 articles for inclusion in the meta-analytic review.

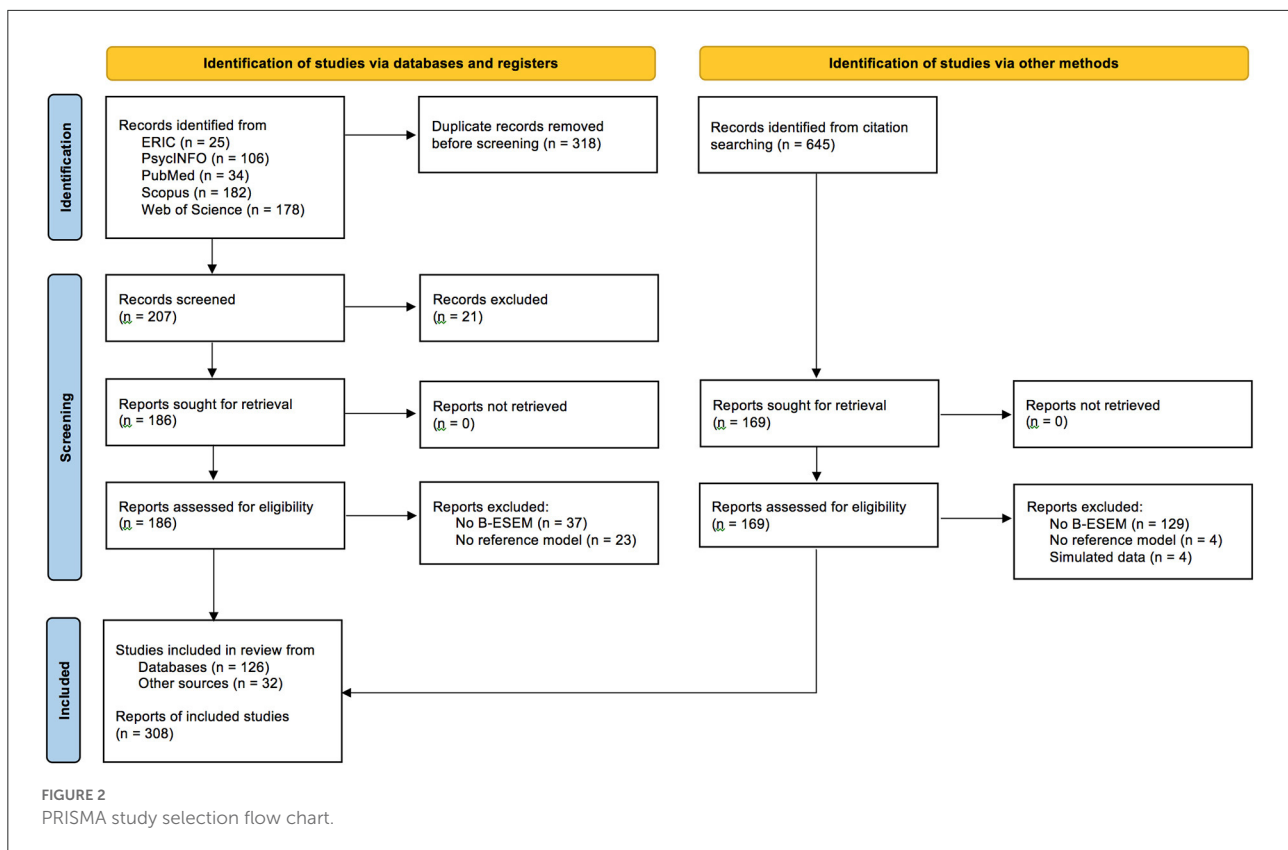
Second, we performed a forward cross-referencing search, using Google Scholar to identify studies that cited the influential article of [Morin et al. \(2016a\)](#) up until December 31, 2021. We read the titles and abstracts of the 723 citing studies and retrieved the full texts of 169 of these reports. After the full texts were read, 137 records were excluded because the studies did not examine a B-ESEM representation (129 removals), did not include a reference model (4 removals), or used simulated data (4 removals). The remaining 32 studies met all inclusion criteria and were thus included in the review.

In summary, the literature search resulted in a total of 158 studies: 126 from the database search and 32 from the forward search. [Figure 2](#) presents the PRISMA study selection flow diagram ([Page et al., 2021](#)). The included studies reported 308 comparisons of B-ESEM representations to reference models, which were subsequently coded.

Coding information from the retrieved studies

Once the studies for inclusion were selected, two trained raters used the coding scheme presented in [Table 3](#) to code a random subset of the 308 identified reports (10 percent; $n = 31$ reports) independently and in duplicate. Coded information included publication characteristics, measurement characteristics, and goodness-of-fit indices. Publication characteristics were coded as the first author and publication year. Measurement characteristics were coded as sample size, target construct, and scale name and abbreviation, as well as the number of items, specific factors, and general factors. Goodness-of-fit indices were coded separately for one-factor, CFA, ESEM, H-CFA, H-ESEM, B-CFA, and B-ESEM model representations; indices included CFI, TLI, RMSEA, SRMR, and the χ^2/df ratio.

To illustrate our coding decisions, examples how we applied the coding scheme may help. For instance, [Rodrigues et al. \(2020\)](#) reported the fit of model representations with (a) one general and two specific factors, (b) one general and six specific factors, and (c) two general and six specific factors for the Behavioral Regulation in Sport Questionnaire and the Behavioral Regulation in Exercise Questionnaire. Because this meta-analytic review aimed to estimate the influence of factor number on model fit, we coded each model separately. Similarly, [Tóth-Király et al. \(2019\)](#) reported the model fit of representations with one or two general factors of the Basic Psychological Need Satisfaction and Frustration Scale. We coded each representation separately to allow for comparison. Generally, model fit was coded separately for studies that tested models with varying numbers of specific and/or general factors (e.g., [Arias et al., 2016](#); [Rodenacker et al., 2017](#); [Gu et al., 2020](#);



Frutos, 2021; Yi et al., 2021) and with varying item numbers. For example, Bianchi and Verkuilen (2021) examined the Green et al. Paranoid Thoughts Scale (GPTS) in its original 32-item version, a revised 18-item version, and an 8-item version. Model fit for each version was coded independently to allow for estimation of the influence of item number on the goodness-of-fit indices. Model fit was also coded separately for studies that used more than one sample (e.g., Neff et al., 2019; Howard et al., 2020; Longo et al., 2020; Vaughan et al., 2020) or measurement time (e.g., Stenling et al., 2018; Cece et al., 2019; Garn et al., 2019; Neff et al., 2021b). Section Research question 1: Description of B-ESEM studies provides a complete description of all coded study information.

Calculating interrater reliability

To calculate interrater reliability and agreement of the literature search and the literature coding, we used an intraclass correlation coefficient (ICC) for continuous scales and Cohen's kappa coefficient (κ) for nominal scales. Table 4 presents all estimates. ICC and κ estimates tend to be robust when there are exactly two raters, as in our case, who searched and coded the studies independently and in duplicate. Consensus

was reached *via* discussion when coding conflicts emerged. Following the recommendations of Koo and Li (2016), ICC estimates were calculated together with their 95% confidence intervals based on a mean-rating ($k = 2$), absolute-agreement, two-way mixed-effects model which can generally be judged as moderate (0.50–0.75), good (0.75–0.90), and excellent (>0.90) reliability. Following recommendations of Landis and Koch (1977), standard errors of Cohen's κ were calculated to compute the 95% confidence intervals around κ which can generally be judged as moderate (0.41–0.60), substantial (0.61–0.80), and almost perfect (>0.80) agreement.

Analyses for the literature search indicated substantial to almost perfect agreement for identification, $\kappa = 0.990$ (95% CI = 0.981; 0.999), screening, $\kappa = 0.881$ (95% CI = 0.659; 1.000), and eligibility, $\kappa = 1.000$ (95% CI = 1.000; 1.000). Analyses for the literature coding were performed separately for the continuous and nominal variables: the continuous scales were publication year, number of items, number of specific factors, number of general factors, and all goodness-of-fit indices, with an ICC = 0.923 (95% CI = 0.901; 0.932); the remaining scales were nominal, with $\kappa = 0.976$ (95% CI = 0.727; 1.000). In summary, these estimates indicate almost perfect agreement (Landis and Koch, 1977) and excellent reliability (Koo and Li, 2016).

TABLE 3 Coding scheme.

Main category	Sub-Category	Anchor example
Publication characteristics		
Author	Name of first author	Haugen
Publication year	Coded as year	in press
Measurement characteristics		
Sample size	Sample size <i>N</i>	333
Construct	Target construct	Group cohesion
Scale properties	Scale name and abbreviation	Group environment questionnaire (GEQ)
	Number of items used	18
	Number of specific factors	4
	Number of general factors	1
Goodness-of-Fit indices		
One-factor	χ^2	488.153
	<i>df</i>	135
	CFI	0.831
	TLI	0.810
	RMSEA	0.089
	SRMR	0.063
CFA	χ^2	291.702
	<i>df</i>	129
	CFI	0.922
	TLI	0.908
	RMSEA	0.062
	SRMR	0.049
ESEM	χ^2	155.324
	<i>df</i>	87
	CFI	0.967
	TLI	0.943
	RMSEA	0.049
	SRMR	0.028
H-CFA	χ^2	302.934
	<i>df</i>	130
	CFI	0.917
	TLI	0.903
	RMSEA	0.063
	SRMR	0.050
H-ESEM	χ^2	153.571
	<i>df</i>	88
	CFI	0.969
	TLI	0.945
	RMSEA	0.047
	SRMR	0.028
B-CFA	χ^2	295.590
	<i>df</i>	118
	CFI	0.915
	TLI	0.890
	RMSEA	0.067

(Continued)

TABLE 3 (Continued)

Main category	Sub-Category	Anchor example
	SRMR	0.053
B-ESEM	χ^2	173.867
	<i>df</i>	73
	CFI	0.952
	TLI	0.899
	RMSEA	0.064
	SRMR	0.024

CFI, comparative fit index; TLI, Tucker-Lewis index, RMSEA, root mean square error of approximation, SRMR, standardized root mean squared residual. CFA, confirmatory factor analysis; ESEM, exploratory structural equation modeling; H-CFA, hierarchical confirmatory factor analysis; H-ESEM, hierarchical exploratory structural equation modeling; B-CFA, bifactor confirmatory factor analysis; B-ESEM, bifactor structural equation modeling.

Meta-analyzing the fit indices

We meta-analyzed the fit indices in two steps. First, we computed average estimates of the goodness-of-fit indices of each model. Mean differences between models were calculated using one-way analyses of variance. Missing values were deleted casewise. Second, we estimated the effects of sample size, item number, number of specific factors, and number of general factors on the fit indices using within-study and between-study analyses. Within-study analyses included (a) descriptive analyses of two-tailed Pearson correlation coefficients and (b) aggregated changes of model fit as a result of changes in B-ESEM model structure. Between-study analysis included (a) an outlier detection analysis using the median absolute deviation approach with the formulae reported in Miller's (1991) and Leys et al. (2013) very conservative threshold 3 and (b) an unrestricted weighted least squares meta-regression analysis (Stanley and Doucouliagos, 2017) to estimate the relative influence of sample size, item number, and factor number on model fit.

Results and discussion

Research question 1: Description of B-ESEM studies

Research question 1 asked, "Which domains, constructs, and scales are targeted in studies adopting a B-ESEM framework?" The 158 studies included in the present analysis offered a total of 308 reports of B-ESEM model fit. Total sample size was 778,624 participants, with a mean sample size of 2,528.00 ($SD = 25,492.06$). On average, B-ESEM models were composed of 24.62 items ($SD = 17.23$), 4.62 specific factors (2.96), and 1.05 general factors (0.26). B-ESEM representations were compared to representations from B-CFA in 221 reports, H-ESEM in 25 reports, H-CFA in 57 reports, ESEM in 266 reports, CFA in

TABLE 4 Interrater reliability and agreement of the literature search and coding.

Step	Category	Coefficient	Estimate	95% confidence interval
Literature search	Identification	κ	0.990	0.981–0.999
	Screening	κ	0.881	0.659–1.000
	Eligibility	κ	1.000	1.000–1.000
Literature coding	Continuous	ICC	0.923	0.901–0.932
	Categorical	κ	0.976	0.727–1.000

κ , Cohen's kappa coefficient; ICC, intraclass correlation coefficient.

265 reports, and a one-factor model in 123 reports. Concerning publication language, 151 of the 158 included studies were written in English, 4 in Spanish, and 1 each in French, German, and Hungarian. Concerning publication type, 154 of the 158 included studies were journal articles, 3 were doctoral theses, and 1 was an unpublished manuscript. Table 5 presents a description of all included studies clustered into six domains.

The first domain of *learning and instruction* includes the constructs of cooperative learning (Fernandez-Rio et al., 2022) and instructional quality (Scherer et al., 2016).

The second domain of *motivation and emotion* includes the constructs academic motivation (Litalien et al., 2017; Guay and Bureau, 2018; Gordeeva et al., 2020; Howard et al., 2020; Kartal, 2020; Guay et al., 2021; Dierendonck et al., 2022), sport motivation (Appleton et al., 2016; Milton et al., 2018; Stenling et al., 2018; Cece et al., 2019; Méndez-Giménez et al., 2020; Rodrigues et al., 2020), work motivation (Burk and Wiese, 2018; Calkins, 2018; Howard et al., 2018, 2020, 2021; Gegenfurtner and Quesada-Pallarès, 2022), job satisfaction (Sutherland, 2020), affective commitment (Perreira et al., 2018), work engagement (Gillet et al., 2019; Huyghebaert-Zouaghi et al., 2021a, 2022), teacher engagement (Perera et al., 2018b), student engagement (Hoi and Hang, 2021; Dierendonck et al., 2022; Tomás et al., 2022), basic psychological needs (Stenling et al., 2015; Sánchez-Oliva et al., 2017; Tóth-Király et al., 2018, 2019; Bhavsar et al., 2019, 2020; Garn et al., 2019; Burgueño et al., 2020a,b; Cromhout, 2020; Gillet et al., 2020; Gucciardi et al., 2020; Huyghebaert-Zouaghi et al., 2021b; Rodrigues et al., 2021), subjective task value (Fadda et al., 2020b; Part et al., 2020), flow (Kyriazos et al., 2018b; Gu et al., 2020), interest (Garn, 2017), locus of causality (Howard et al., 2020), attitudes (Deemer et al., 2014), purpose (Summers and Falco, 2020), self-efficacy (Barbaranelli et al., 2018; Dominguez-Lara et al., 2019), emotion regulation (Clifton et al., 2020; Hanley et al., 2020; Lauriola et al., 2021), happiness (Appiah et al., 2020), hope (Krafft et al., 2020), anxiety (Lohbeck and Petermann, 2019), fear (Jastrzebski et al., 2020), and loneliness (Grygiel et al., 2019).

The third domain of *self and identity* includes the constructs of self-compassion (Tóth-Király et al., 2017; Benda, 2018; Neff et al., 2018, 2019, 2021a,b), self-concept (Morin et al., 2016a; Arens et al., 2021), self-perception (Chung et al., 2016; Arens

and Morin, 2017; Giotsa and Kyriazos, 2019), body checking (Maiano et al., 2021), big five personality traits (Lee et al., 2017; Arias et al., 2018), multicultural personality (Korol et al., 2018), psychopath personality (Gu et al., 2017; McLarnon and Tarraf, 2017, 2021; Somma et al., 2019; Gomez et al., 2020b; Vaughan et al., 2020), conspiracy beliefs (García-Garzón et al., 2020), paranoid thoughts (Bianchi and Verkuilen, 2021), character strength (Ng et al., 2017; Wang et al., 2021), consideration of future consequences (McKay et al., 2016), morningness (Morin et al., 2016b; Díaz-Morales and Parra-Robledo, 2018), compassion (Halamová et al., 2020; Pommier et al., 2020), emotional intelligence (Esnaola et al., 2018; Pirsoul et al., 2022), intelligence (Lecerf and Canivez, 2018), life skills (Cronin and Allen, 2017; Jaotombo, 2019; Choisy et al., 2021), mental toughness (Bédard-Thom and Guay, 2018; Schmid et al., 2018; Kawabata et al., 2021), and resilience (Decroos et al., 2017; Perera and Ganguly, 2018; Dai et al., 2019).

The fourth dimension of *depression and wellbeing* includes the constructs of depression (Borges et al., 2017; Volmer et al., 2019; Bianchi, 2020; Bianchi and Schonfeld, 2020; Cano-García et al., 2020; Gomez et al., 2020a; Nixon et al., 2020; Vaughan et al., 2020; Høstmælingen et al., 2021; Jovanovic et al., 2021), burnout (Isoard-Gauthier et al., 2018; Bianchi, 2020; Sakakibara et al., 2020; Trógolo et al., 2020; Doherty et al., 2021; Tóth-Király et al., 2021), positive thoughts (Appiah et al., 2020), wellbeing (Myers et al., 2016; Fadda et al., 2017, 2020a; Morin et al., 2017; Schutte and Wissing, 2017; Espinoza et al., 2018; Kyriazos et al., 2018a; Lamborn et al., 2018; Perera et al., 2018a; Rogoza et al., 2018; Silverman et al., 2018; Ferentinos et al., 2019; Cromhout, 2020; Longo et al., 2020; Reinhardt et al., 2020a,b), workaholism (Huyghebaert-Zouaghi et al., 2022), stress (Morin et al., 2016c; Portoghese et al., 2020), stress disorder (Fresno et al., 2020), anxiety disorder (Deller et al., 2020; Styck et al., 2021), problem behavior (Lahey et al., 2018; Hukkelberg, 2019; Hukkelberg and Ogden, 2020; Gomez et al., 2021), and attention deficit hyperactivity disorder (Arias et al., 2016; Rodenacker et al., 2017; Frutos, 2019, 2021; Gomez and Stavropoulos, 2021; Yi et al., 2021).

The fifth dimension of *interpersonal relations* includes the constructs of romantic relationships (Vajda et al., 2019; Goodboy et al., 2021), parenting (Ratelle et al., 2018), group cohesion

TABLE 5 Study description.

Domain	Construct	Scale	Included studies
Learning and instruction	Cooperative learning	Cooperative learning scale	Fernandez-Rio et al., 2022
	Instructional quality	Instructional quality scale (as measured in PISA)	Scherer et al., 2016
Motivation and emotion	Academic motivation	Academic motivation scale (AMS)	Dierendonck et al., 2022 Guay and Bureau, 2018 Guay et al., 2021 Howard et al., 2020 Kartal, 2020 Litalien et al., 2017
		Academic self-regulation questionnaire (SRQ-A)	Gordeeva et al., 2020
	Sport motivation	Behavioral regulation in sport questionnaire (BRSQ)	Rodrigues et al., 2020 Stenling et al., 2018
		Youth behavioral regulation in sport questionnaire	Cece et al., 2019
		Behavioral regulation in exercise questionnaire (BREQ)	Rodrigues et al., 2020
		Cuestionario tridimensional de competencia percibida	Méndez-Giménez et al., 2020
	Work motivation	Empowering and disempowering motivational climate questionnaire (EDMCQ)	Appleton et al., 2016 Milton et al., 2018
		Multidimensional work motivation scale (MWMS)	Howard et al., 2018 Howard et al., 2020 Howard et al., 2021
		Transfer motivation questionnaire (TMQ)	Gegenfurtner and Quesada-Pallarès, 2022
	Job satisfaction	Faculty motivation to teach in higher education	Calkins, 2018
		Work-Related motivational orientations measure	Burk and Wiese, 2018
	Affective commitment	Leader satisfaction assessment (LSA)	Sutherland, 2020
		Minnesota satisfaction questionnaire (MSQ)	Sutherland, 2020
	Work engagement	Workplace affective commitment multidimensional questionnaire (WACMQ-S)	Perreira et al., 2018
		Utrecht work engagement scale (UWES-9)	Gillet et al., 2019 Huyghebaert-Zouaghi et al., 2021a Huyghebaert-Zouaghi et al., 2022
	Teacher engagement	Engaged teacher scale (ETS)	Perera et al., 2018b
Student engagement	Student engagement scale (SES)	Tomás et al., 2022	
	Engagement in the classroom scale	Dierendonck et al., 2022	
	Schoolwork engagement inventory (EDA)	Tomás et al., 2022	
Basic psychological needs	Online student engagement questionnaire	Hoi and Hang, 2021	
	Basic psychological needs scale (BPNS)	Cromhout, 2020	
	Basic psychological need satisfaction and frustration scale (BPNSFS)	Garn et al., 2019 Tóth-Király et al., 2018	
	Basic psychological needs at work scale (BPNW)	Tóth-Király et al., 2019	
	Work-Related basic need satisfaction scale (W-BNS)	Sánchez-Oliva et al., 2017	
	Psychological need states at work-scale (PNSW-S)	Gillet et al., 2020	
Basic psychological needs in exercise scale (BPNES)	Huyghebaert-Zouaghi et al., 2021b Rodrigues et al., 2021		

(Continued)

TABLE 5 (Continued)

Domain	Construct	Scale	Included studies
		Psychological need states in sport-scale (PNSS-S)	Bhavsar et al., 2020
		Multidimensional perceived autonomy support scale in physical education	Burgueño et al., 2020b
		Needs-Support behaviors scale (NSBS)	Gucciardi et al., 2020
		Interpersonal supportiveness scale—coach (ISS-C)	Stenling et al., 2015
		Tripartite measure of interpersonal behaviors of coaches (TMIB-C)	Bhavsar et al., 2019
		Basic psychological need satisfaction in active commuting to and from school (BPNS-ACS)	Burgueño et al., 2020a
	Subjective task value	Subjective task value	Part et al., 2020
		Math-Related value beliefs scale	Fadda et al., 2020b
	Flow	Flow short scale (FSS)	Kyriazos et al., 2018b
		Work-Related flow inventory (WOLF)	Gu et al., 2020
	Interest	Situational interest scale	Garn, 2017
	Locus of causality	Revised perceived locus of causality (PLOC-R)	Howard et al., 2020
	Attitudes	Subjective science attitude change measures (SSACM)	Deemer et al., 2014
	Purpose	Measure of adolescent purpose (MAP)	Summers and Falco, 2020
	Self-efficacy	Work self-efficacy (W-SE)	Barbaranelli et al., 2018
		Escala de autoeficacia docente (EAD)	Dominguez-Lara et al., 2019
	Emotion regulation	Emotional processing scale (EPS-25)	Lauriola et al., 2021
		Metacognitive processes of decentering (MPoD)	Hanley et al., 2020
		Emotional responding	Clifton et al., 2020
	Happiness	Affectometer-2 (AFM-2)	Appiah et al., 2020
	Hope	Perceived hope scale (PHS)	Krafft et al., 2020
	Anxiety	Anxiety questionnaire for students (AFS)	Lohbeck and Petermann, 2019
	Fear	Death and dying anxiety inventory (FVTS)	Jastrzebski et al., 2020
	Loneliness	De Jong gierveld loneliness scale (DJGLS)	Grygiel et al., 2019
Self and identity			
	Self-compassion	Self-Compassion scale (SCS)	Neff et al., 2018
			Neff et al., 2019
			Tóth-Király et al., 2017
			Benda, 2018
		Self-Compassion scale—youth version (SCS-Y)	Neff et al., 2021a
		State self-compassion scale—long form (SSCS-L)	Neff et al., 2021b
	Self-concept	Academic self-concept (ASC)	Arens et al., 2021
		Strengths and difficulties questionnaire (SDQ)	Morin et al., 2016a
	Self-perception	Self-Perception profile for children (SPPC)	Arens and Morin, 2017
		Physical self-perception profile (PSPP)	Chung et al., 2016
		Early childhood parental acceptance-rejection questionnaire (ECPARQ)	Giotsa and Kyriazos, 2019
	Body checking	Body checking questionnaire (BCQ)	Maiano et al., 2021
		Body checking cognitions scale (BCCS)	Maiano et al., 2021
	Personality, big five	International personality item pool (IPIP)	Lee et al., 2017
		International personality item pool—short form (Mini-IPIP)	Arias et al., 2018
	Personality, multicultural	Multicultural personality inventory—short form (MPI-SF)	Korol et al., 2018

(Continued)

TABLE 5 (Continued)

Domain	Construct	Scale	Included studies	
	Personality, psychopath	Short dark triad (SD3)	McLarnon and Tarraf, 2017 McLarnon and Tarraf, 2021 Vaughan et al., 2019	
		Dirty dozen (DD)	McLarnon and Tarraf, 2017	
		Triarchic psychopathy measure (TriPM)	Somma et al., 2019	
		Machiavellian personality scale (MPS)	Gu et al., 2017	
		Personality inventory for DSM-5—brief form (PID-5-BF)	Gomez et al., 2020b	
		Conspiracy beliefs	Generic conspiracist belief scale (GCB)	García-Garzón et al., 2020
	Paranoid thoughts	Green et al. paranoid thoughts scale (GPTS)	Bianchi and Verkuilen, 2021	
	Character strength	Encouragement character strength scale (ECSS)	Wang et al., 2021	
		Values in action inventory of strengths (VIA-IS)	Ng et al., 2017	
	Consideration of future consequences	Consideration of future consequences scale-14 (CFC-12)	McKay et al., 2016	
	Morningness	Composite scale of morningness (CSM)	Díaz-Morales and Parra-Robledo, 2018	
			Morin et al., 2016b	
	Compassion	Compassionate engagement and action scales (CEAS)	Halamová et al., 2020	
		Compassion scale (CS)	Pommier et al., 2020	
	Emotional intelligence	Emotional quotient inventory: youth version short (EQ-i: YV-S)	Esnaola et al., 2018	
		Profile of emotional competence (PEC)	Pirsoul et al., 2022	
	Intelligence	Wechsler intelligence scale for children—fifth edition (WISC-V)	Lecerf and Canivez, 2018	
	Life skills	Life skills scale for sport (LSSS)	Cronin and Allen, 2017	
		French psychological capital questionnaire (F-PCQ-24)	Choisay et al., 2021	
		Fonctionnement optimal psychologique (FOP)	Jaotombo, 2019	
Grit	Grit-Original scale (Grit-O)	Van Zyl et al., 2020		
Mental toughness	Mental toughness inventory (MTI)	Bédard-Thom and Guay, 2018		
		Schmid et al., 2018		
		Kawabata et al., 2021		
Resilience	Mental toughness questionnaire-48 (MTQ48)	Decroos et al., 2017		
	Characteristics of resilience in sports teams (CREST)	Dai et al., 2019		
	Connor–Davidson resilience scale (CD-RISC)	Perera and Ganguly, 2018		
Depression and wellbeing	Depression	Depression anxiety stress scales-21 (DASS-21)	Gomez et al., 2020a Jovanovic et al., 2021 Vaughan et al., 2020 Volmer et al., 2019	
		Patient health questionnaire (PHQ-9 and PHQ-15)	Bianchi, 2020 Cano-García et al., 2020	
		Occupational depression inventory (ODI)	Bianchi and Schonfeld, 2020	
		Depression indicators scale-children and adolescents (BAID-IJ)	Borges et al., 2017	
		Beck depression inventory-II (BDI-II)	Høstmælingen et al., 2021	
		Hamilton depression rating scale (HDRS17)	Nixon et al., 2020	
		Burnout	Maslach burnout inventory—human services survey (MBI-HSS)	Doherty et al., 2021

(Continued)

TABLE 5 (Continued)

Domain	Construct	Scale	Included studies
		Burnout assessment tool (BAT)	Sakakibara et al., 2020
		Burnout and work engagement (with items of MBI and UWES)	Trógolo et al., 2020
		Athlete burnout scale (ABO-S)	Isoard-Gauthier et al., 2018
		School burnout inventory (SBI)	Tóth-Király et al., 2021
		Shirom-Melamed burnout measure (SMBM)	Bianchi, 2020
	Positive thoughts	Automatic thoughts questionnaire—positive (ATQ-P)	Appiah et al., 2020
	Wellbeing	Mental health continuum—short form (MHC-SF)	Ferentinos et al., 2019
			Lamborn et al., 2018
			Longo et al., 2020
			Reinhardt et al., 2020a
			Reinhardt et al., 2020b
			Rogoza et al., 2018
			Schutte and Wissing, 2017
			Silverman et al., 2018
		Questionnaire for eudaimonic wellbeing (QEWB)	Cromhout, 2020
			Fadda et al., 2017
			Fadda et al., 2020a
		Index of psychological wellbeing at work (IPWBW)	Morin et al., 2017
		Scales of psychological wellbeing (SPWB)	Espinoza et al., 2018
		Peer and community relational health indices (RHIP and RHIC)	Cromhout, 2020
		Scale of positive and negative experience (SPANÉ)	Kyriazos et al., 2018a
		Interpersonal, community, occupational, physical, psychological, economic scale (I COPPE)	Myers et al., 2016
		World health organization quality of life scale (WHOQOL-BREF)	Perera et al., 2018a
	Workaholism	Dutch work addiction scale (DUWAS)	Huyghebaert-Zouaghi et al., 2022
	Stress	University stress scale (USS)	Portoghese et al., 2020
		Détresse psychologique au travail (DPT)	Morin et al., 2016c
	Stress disorder	Posttraumatic stress disorder checklist—5 (PCL—5)	Fresno et al., 2020
	Anxiety disorder	Multidimensional social anxiety response inventory-21 (MSARI-21)	Deller et al., 2020
		State–Trait inventory of cognitive and somatic anxiety (STICSA)	Styck et al., 2021
	Problem behavior	Eyberg child behavior inventory (ECBI)	Hukkelberg, 2019
		Home and community social behavior scales (HCSBS)	Hukkelberg and Ogden, 2020
		Symptom checklist-9–revised (SCL-90-R)	Gomez et al., 2021
		Young adult version of the diagnostic interview for children (YA-DISC)	Lahey et al., 2018
	ADHD	ADHD rating scale-IV (ADHD RS-IV)	Yi et al., 2021
		ADHD questionnaire, adapted from DSM-5	Arias et al., 2016
			Frutos, 2021
		Adult ADHD self-report scale symptom checklist (ASRS)	Gomez and Stavropoulos, 2021
		Diagnostik-System für psychische störungen II (DISYPS-II)	Rodenacker et al., 2017

(Continued)

TABLE 5 (Continued)

Domain	Construct	Scale	Included studies
		Inventario de comportamiento infantil y adolescente (CABI)	Frutos, 2019
Interpersonal relations	Romantic relationships	Dyadic adjustment scale (DAS)	Vajda et al., 2019
		Relational uncertainty scale	Goodboy et al., 2021
	Parenting	Parental structure scale	Ratelle et al., 2018
	Group cohesion	Group environment questionnaire (GEQ)	Haugen et al., 2021
	Working alliance	Working alliance inventory short form (WAI-S)	Hukkelberg and Ogden, 2019
	Work teams	Role ambiguity scale (RAS)	Leo et al., 2017
	Supervision	Supervisee levels questionnaire (SLQ-R)	Junga et al., 2019
	Perceived social support	Social provisions scale (SPS)	Perera, 2016
Other	Motoric skills	Test of gross motor development-third edition (TGMD-3)	Garn and Webster, 2021
	Scar evaluation	Patient-Reported scar evaluation questionnaire (PR-SEQ)	Sen et al., 2015

TABLE 6 Mean (and standard deviation) estimates of the goodness-of-fit indices per model.

	χ^2/df	CFI	TLI	RMSEA	SRMR
One-factor	14.506 (18.531)	0.748 (0.161)	0.715 (0.174)	0.106 (0.040)	0.093 (0.043)
CFA	6.339 (10.551)	0.898 (0.092)	0.881 (0.095)	0.073 (0.033)	0.061 (0.041)
ESEM	3.869 (3.665)	0.952 (0.051)	0.924 (0.085)	0.056 (0.037)	0.030 (0.014)
H-CFA	4.190 (2.560)	0.886 (0.071)	0.872 (0.077)	0.066 (0.028)	0.069 (0.029)
H-ESEM	2.940 (1.513)	0.966 (0.020)	0.950 (0.027)	0.051 (0.026)	0.023 (0.006)
B-CFA	4.891 (3.882)	0.918 (0.071)	0.895 (0.080)	0.070 (0.030)	0.062 (0.079)
B-ESEM	2.697 (1.929)	0.971 (0.035)	0.948 (0.056)	0.043 (0.017)	0.022 (0.012)
$F_{(1,6)}$	33.563	131.653	96.665	69.902	29.240
p	<0.001	<0.001	<0.001	<0.001	<0.001
Partial η^2	0.848	0.956	0.942	0.921	0.830
90% CI	0.442–0.907	0.803–0.973	0.744–0.963	0.666–0.951	0.396–0.896

CFI, comparative fit index; TLI, Tucker-Lewis index, RMSEA, root mean square error of approximation, SRMR, standardized root mean squared residual. CFA, confirmatory factor analysis; ESEM, exploratory structural equation modeling; H-CFA, hierarchical confirmatory factor analysis; H-ESEM, hierarchical exploratory structural equation modeling; B-CFA, bifactor confirmatory factor analysis; B-ESEM, bifactor structural equation modeling.

(Haugen et al., 2021), working alliance (Hukkelberg and Ogden, 2019), work teams (Leo et al., 2017), supervision (Junga et al., 2019), and perceived social support (Perera, 2016).

The sixth and last category includes two constructs that did not fit the aforementioned five domains: motoric skills (Garn and Webster, 2021) and scar evaluation (Sen et al., 2015).

The 158 included studies psychometrically tested a total of 135 different scales. Among the most often-investigated constructs are wellbeing ($n = 17$), basic psychological needs ($n = 14$ studies), depression ($n = 10$), academic motivation ($n = 7$), psychopathic personality ($n = 7$), sport motivation ($n = 7$), attention deficit hyperactivity disorder ($n = 6$), burnout

($n = 6$), self-compassion ($n = 6$), and work motivation ($n = 6$). Scales whose factorial structures were frequently examined using a B-ESEM approach include the Mental Health Continuum—Short Form (MHC-SF), addressed in eight studies, the Academic Motivation Scale (AMS), addressed in six studies, and the Self-Compassion Scale (SCS), addressed in six studies.

Research question 2: Model fit

Research question 2 asked, “What is the model fit of B-ESEM representations in comparison to CFA, ESEM,

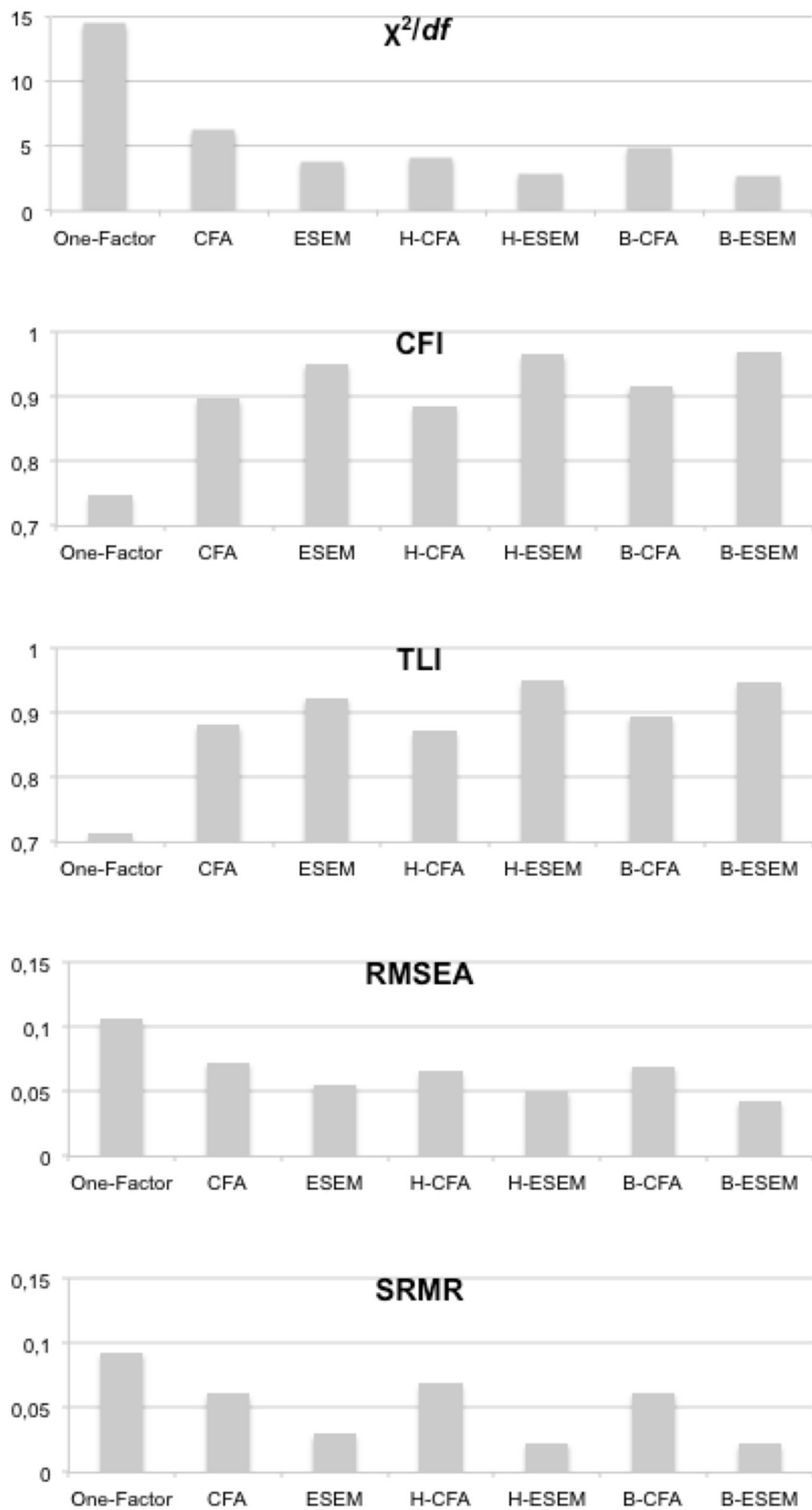


FIGURE 3 Goodness-of-fit indices per model representation.

TABLE 7 Correlation matrix.

Variable	01	02	03	04	05	06	07	08	09	10	11	12	13	14	15	16
01 Sample size	–															
02 Item number	0.27	–														
03 Specific factor number	0.37	0.69	–													
04 General factor number	–0.01	0.10	0.18	–												
05 One-factor χ^2/df	0.81	–0.21	–0.12	0.08	–											
06 One-factor CFI	0.06	0.14	0.05	–0.34	0.05	–										
07 One-factor TLI	0.06	0.19	0.10	–0.32	0.05	0.97	–									
08 One-factor RMSEA	0.09	–0.47	–0.32	0.16	0.38	–0.25	–0.27	–								
09 One-factor SRMR	–0.08	0.25	0.15	0.25	0.15	–0.74	–0.75	0.56	–							
10 CFA χ^2/df	0.38	–0.08	0.03	0.03	0.89	0.09	0.10	0.20	–0.03	–						
11 CFA CFI	–0.03	–0.16	0.02	–0.13	0.23	0.71	0.70	0.14	–0.30	–0.02	–					
12 CFA TLI	–0.02	–0.12	0.05	–0.13	0.24	0.71	0.71	0.13	–0.30	–0.02	0.96	–				
13 CFA RMSEA	–0.09	–0.20	–0.19	0.00	0.06	–0.19	–0.20	0.56	0.32	0.54	–0.44	–0.32	–			
14 CFA SRMR	–0.04	0.02	–0.13	0.00	–0.17	–0.15	–0.71	–0.03	0.16	0.00	–0.31	–0.75	0.24	–		
15 ESEM χ^2/df	0.66	–0.18	–0.24	–0.01	0.72	0.05	0.04	0.23	–0.05	0.48	0.00	–0.01	0.21	–0.05	–	
16 ESEM CFI	–0.06	–0.07	0.12	–0.08	0.11	0.51	0.49	0.06	–0.34	–0.02	0.73	0.71	–0.17	–0.29	–0.17	–
17 ESEM TLI	–0.02	–0.03	0.06	–0.07	0.10	0.57	0.56	0.03	–0.36	–0.03	0.54	0.53	–0.13	–0.71	–0.17	0.71
18 ESEM RMSEA	–0.05	–0.18	–0.19	–0.02	0.11	–0.10	–0.12	0.61	0.28	0.03	–0.05	–0.06	0.33	0.26	17	–0.20
19 ESEM SRMR	–0.01	–0.07	–0.34	–0.09	–0.23	–0.31	–0.33	–0.18	0.17	–0.10	–0.68	–0.69	0.33	0.37	0.11	–0.83
20 H-CFA χ^2/df	0.66	–0.35	–0.12	–0.16	0.76	–0.16	–0.17	0.38	0.00	0.75	0.11	0.06	0.39	–0.35	0.64	0.23
21 H-CFA CFI	–0.18	–0.07	–0.28	–0.33	–0.37	0.84	0.84	–0.15	–0.43	–0.10	0.68	0.69	–0.13	–0.73	–0.14	0.78
22 H-CFA TLI	–0.15	–0.02	–0.25	–0.32	–0.39	0.87	0.85	–0.18	–0.42	–0.08	0.64	0.67	–0.14	–0.73	–0.14	0.75
23 H-CFA RMSEA	–0.13	–0.46	–0.28	0.02	0.18	–0.23	–0.25	0.44	–0.25	0.44	0.00	–0.03	0.90	0.45	0.24	0.04
24 H-CFA SRMR	–0.27	–0.03	–0.03	0.04	–0.15	–0.66	–0.66	–0.44	–0.02	–0.15	–0.26	–0.45	0.26	0.50	–0.03	–0.49
25 H-ESEM χ^2/df	0.16	–0.46	–0.42	–	0.38	0.06	0.04	0.21	–0.68	0.41	–0.07	–0.12	0.18	–0.65	0.93	–0.44
26 H-ESEM CFI	0.09	0.12	0.25	–	–0.08	0.66	0.73	–0.44	–0.04	0.13	0.71	0.60	0.12	–0.42	–0.43	0.96
27 H-ESEM TLI	0.09	0.20	0.33	–	–0.18	0.71	0.71	–0.56	0.09	0.11	0.67	0.62	0.06	–0.27	–0.48	0.96
28 H-ESEM RMSEA	–0.32	–0.52	–0.49	–	0.10	0.05	0.02	0.44	–0.51	0.35	–0.14	–0.24	0.79	–0.27	0.69	–0.15
29 H-ESEM SRMR	–0.93	0.49	–0.41	–	–0.89	0.01	0.04	0.16	0.31	–0.86	–0.42	–0.45	0.72	0.56	0.01	–0.75
30 B-CFA χ^2/df	0.64	–0.19	–0.06	0.01	0.79	0.05	0.06	0.21	–0.10	0.80	0.03	0.03	0.27	–0.11	0.79	0.04
31 B-CFA CFI	0.15	–0.29	–0.28	–0.05	0.28	0.72	0.71	0.20	–0.21	0.11	0.64	0.61	–0.10	–0.09	0.08	0.39
32 B-CFA TLI	0.17	–0.22	–0.25	–0.04	0.30	0.74	0.73	0.17	–0.21	0.11	0.61	0.60	–0.14	–0.41	0.05	0.36
33 B-CFA RMSEA	–0.26	–0.18	–0.06	–0.07	–0.06	–0.14	–0.15	0.62	0.16	0.08	0.00	0.01	0.70	–0.09	0.05	0.10
34 B-CFA SRMR	–0.17	0.19	0.29	–0.03	–0.46	–0.41	–0.39	–0.30	–0.04	–0.20	–0.34	–0.01	–0.13	–0.03	–0.19	–0.02
35 B-ESEM χ^2/df	0.67	–0.16	–0.20	–0.02	0.66	–0.03	–0.04	0.20	0.07	0.42	–0.02	–0.02	0.15	–0.03	0.85	–0.18
36 B-ESEM CFI	–0.08	–0.15	0.00	–0.08	0.23	0.53	0.51	0.13	–0.37	0.08	0.64	0.66	–0.06	–0.27	–0.02	0.88
37 B-ESEM TLI	–0.04	–0.08	0.02	–0.09	0.23	0.58	0.56	0.09	–0.35	0.11	0.58	0.57	–0.07	–0.46	0.00	0.74
38 B-ESEM RMSEA	–0.06	–0.13	–0.18	0.00	–0.12	–0.28	–0.30	0.37	0.10	0.01	–0.25	–0.22	0.48	0.26	0.19	–0.44
39 B-ESEM SRMR	0.04	0.16	–0.17	–0.03	–0.44	–0.39	–0.43	–0.37	–0.24	–0.24	–0.54	–0.54	0.12	0.31	–0.12	–0.53

Two-tailed Pearson correlation coefficients.

TABLE 7 (Continued)

		17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32
17	ESEM TLI	-															
18	ESEM RMSEA	-0.16	-														
19	ESEM SRMR	-0.79	0.59	-													
20	H-CFA χ^2/df	0.20	0.08	-0.58	-												
21	H-CFA CFI	0.77	-0.15	-0.55	-0.05	-											
22	H-CFA TLI	0.76	-0.18	-0.57	-0.08	0.99	-										
23	H-CFA RMSEA	-0.05	0.79	0.33	0.40	-0.17	-0.22	-									
24	H-CFA SRMR	-0.52	0.38	0.50	-0.20	-0.40	-0.57	0.58	-								
25	H-ESEM χ^2/df	-0.61	0.57	-0.05	0.43	-0.08	-0.10	0.27	-0.70	-							
26	H-ESEM CFI	0.87	-0.16	-0.74	-0.01	0.89	0.84	0.03	-0.63	-0.35	-						
27	H-ESEM TLI	0.93	-0.26	-0.83	0.00	0.83	0.82	-0.12	-0.30	-0.45	0.98	-					
28	H-ESEM RMSEA	-0.41	0.98	0.50	0.43	-0.13	-0.25	-0.81	-0.32	0.68	-0.17	-0.29	-				
29	H-ESEM SRMR	0.70	0.64	0.99	-0.97	-0.42	-0.70	0.82	0.61	-0.08	-0.75	-0.82	0.46	-			
30	B-CFA χ^2/df	0.03	0.02	-0.15	0.83	-0.22	-0.20	0.45	-0.24	0.38	0.11	0.14	0.34	-0.96	-		
31	B-CFA CFI	0.38	0.06	-0.42	0.16	0.61	0.57	0.07	-0.53	0.04	0.81	0.76	0.09	-0.43	-0.01	-	
32	B-CFA TLI	0.38	0.04	-0.43	0.11	0.61	0.59	0.00	0.90	-0.11	0.54	0.59	-0.25	-0.88	-0.03	0.98	-
33	B-CFA RMSEA	-0.02	0.21	0.11	0.39	-0.21	-0.24	0.91	0.44	0.27	0.05	-0.04	0.80	0.95	0.35	-0.38	-0.42
34	B-CFA SRMR	-0.03	-0.10	-0.04	-0.39	-0.59	-0.59	0.63	0.61	0.40	-0.77	-0.95	0.78	0.83	-0.11	-0.46	-0.47
35	B-ESEM χ^2/df	-0.18	0.11	0.08	0.59	-0.25	-0.24	0.26	-0.12	0.89	-0.55	-0.61	0.70	0.29	0.70	0.07	0.06
36	B-ESEM CFI	0.62	-0.10	-0.67	0.25	0.74	0.69	0.09	-0.10	-0.13	0.86	-0.86	-0.07	-0.83	0.12	0.43	0.39
37	B-ESEM TLI	0.55	-0.10	-0.52	0.21	0.75	0.73	0.01	-0.21	-0.28	0.77	0.83	-0.24	-0.85	0.13	0.40	0.39
38	B-ESEM RMSEA	-0.36	0.35	0.46	0.07	-0.28	-0.29	0.75	0.28	0.50	-0.24	-0.32	0.93	0.78	0.02	-0.11	-0.15
39	B-ESEM SRMR	-0.49	0.25	0.66	-0.53	-0.68	-0.64	0.22	0.22	-0.35	-0.77	-0.74	0.16	0.92	-0.19	-0.53	-0.53

(Continued)

number. Average estimates across reports suggest that, when the number of specific factors changed from two to three, two to six, three to four, or three to six, CFI and TLI increased, while the χ^2/df ratio, RMSEA, and SRMR decreased. Similarly, when the number of general factors changed from one to two, CFI and TLI increased, while the χ^2/df ratio, RMSEA, and SRMR decreased.

Second, between-study analyses were performed to estimate the extent to which model fit is influenced by sample size, item number, and the number of specific and general factors. Between-study analyses included correlation analyses and meta-regression analysis. The correlation analysis shown in [Table 7](#) suggests high correlation coefficients between sample size and the χ^2/df ratio. Prior to the meta-regression, an outlier

TABLE 8 Within-Study analysis of changes in B-ESEM model fit by factor number.

Factor change	Study	$\Delta \chi^2/df$	Δ CFI	Δ TLI	Δ RMSEA	Δ SRMR
2–3 s	Arias et al. (2016)	−0.978	0.016	0.022	−0.016	–
	Frutos (2019)	−1.349	0.008	0.009	−0.009	–
	Frutos (2021)	–	0.009	0.012	−0.016	–
	Giotsa and Kyriazos (2019)	−0.257	0.020	0.022	−0.005	−0.005
	Giotsa and Kyriazos (2019)	−0.467	0.023	0.027	−0.007	−0.007
	Gomez and Stavropoulos (2021)	0.131	0.003	−0.005	0.002	–
	Gu et al. (2020)	−3.458	0.050	0.080	−0.040	–
	Nixon et al. (2020)	−0.069	0.040	0.045	−0.008	–
	Rodenacker et al. (2017)	−0.865	0.004	–	−0.006	–
	Rodenacker et al. (2017)	−0.600	0.003	–	−0.005	–
	Tóth-Király et al. (2018)	−4.647	0.057	0.070	−0.018	–
	Tóth-Király et al. (2018)	−1.067	0.052	0.065	−0.022	–
	Yi et al. (2021)	−0.626	0.008	0.011	−0.017	–
	Average	−1.188	0.023	0.032	−0.013	−0.006
2–6 s	Rodrigues et al. (2020)	−1.235	0.088	0.077	−0.019	−0.021
	Rodrigues et al. (2020)	−1.650	0.098	0.107	−0.024	−0.024
	Tóth-Király et al. (2018)	−8.410	0.098	0.127	−0.044	–
	Tóth-Király et al. (2018)	−1.564	0.074	0.095	−0.041	–
	Average	−3.215	0.090	0.102	−0.032	−0.023
3–4 s	Cromhout (2020)	−0.089	0.016	0.019	−0.005	−0.006
	Cromhout (2020)	0.038	0.000	−0.005	0.002	−0.003
	Cromhout (2020)	−0.284	0.024	0.082	−0.025	−0.008
	Cromhout (2020)	0.276	−0.010	−0.050	0.007	−0.004
	Fadda et al. (2017)	−0.045	0.010	0.006	−0.001	–
	Giotsa and Kyriazos (2019)	−0.080	0.006	0.004	−0.002	−0.003
	Sutherland (2020)	−0.006	0.002	0.001	0.000	–
	Average	−0.027	0.007	0.008	−0.003	−0.005
3–6 s	Espinoza et al. (2018)	−0.583	0.086	0.086	−0.012	–
	Espinoza et al. (2018)	−0.597	0.101	0.099	−0.013	–
	Tóth-Király et al. (2018)	−3.763	0.041	0.057	−0.026	–
	Tóth-Király et al. (2018)	−2.233	0.025	0.033	−0.017	–
	Tóth-Király et al. (2018)	−0.498	0.022	0.030	−0.019	–
	Average	−1.535	0.055	0.061	−0.017	–
1–2 g	Neff et al. (2018)	−0.396	0.000	0.010	−0.010	–
	Rodrigues et al. (2020)	−0.690	0.017	0.017	−0.005	−0.005
	Rodrigues et al. (2020)	−0.314	0.014	0.020	−0.007	−0.005
	Tóth-Király et al. (2018)	−0.093	0.000	−0.002	0.001	–
	Tóth-Király et al. (2018)	−1.437	0.016	0.022	−0.008	–
	Tóth-Király et al. (2018)	−0.243	0.010	0.015	−0.008	–
	Tóth-Király et al. (2019)	0.017	0.000	−0.001	0.000	–
	Average	−0.451	0.008	0.012	−0.005	−0.005

2–3 s, change from two specific to three specific factors; 2–6 s, change from two specific to six specific factors; 3–4 s, change from three specific to four specific factors; 3–6 s, change from three specific to six specific factors; 1–2 g, change from one general factor to two general factors.

TABLE 9 Outlier detection analysis.

Variable	<i>Md</i>	<i>MAD</i>	Interval	<i>N</i>
Sample size	573	396.596	$-616.787 < x_i < 1,762.787$	40
Item number	21	7.413	$-1.239 < x_i < 43.239$	12
Number of specific factor	4	1.483	$-0.449 < x_i < 8.449$	19
Number of general factors	1	0	$1 < x_i < 1$	13

Md, median; *MAD*, median absolute deviation; *N*, number of detected outliers.

detection analysis was conducted to identify studies with outlying values. Analyses were performed separately for sample size, item number, number of specific factors, and number of general factors. Table 9 presents the outcomes of the outlier analysis. For sample size, 40 reports with more than 1,763 participants were identified. For item number, 12 reports examined scales with 44 items or more. For the number of specific factors, 19 reports used B-ESEM representations with nine specific factors or more. For the number of general factors, 13 reports used B-ESEM representations with more than one general factor. These reports were removed prior to the meta-regression analysis.

Table 10 presents the results of the meta-regression. First, the findings indicate that sample size significantly influenced the χ^2/df ratio in all models except H-ESEM. This finding supports simulation study results on the sample-size sensitivity of the χ^2/df ratio. Second, item number influenced (a) CFI and TLI in all models except ESEM, (b) RMSEA in CFA, H-CFA, and H-ESEM, and (c) SRMR in all models except ESEM and H-ESEM. Third, the number of specific factors influenced (a) CFI and TLI in all models except CFA, H-ESEM, and B-ESEM, (b) RMSEA in the CFA, ESEM, H-ESEM, B-CFA, and B-ESEM representations, and (c) SRMR in the ESEM, H-CFA, B-CFA, and B-ESEM representations.

As a cautionary note, goodness-of-fit is a critical component in evaluating support for a model, but it is not the only one. Particularly when fitting a more parsimonious a priori model with a less parsimonious ex-post-facto model, there is danger in simply comparing fit. Similarly, set-ESEM (Marsh et al., 2020) allows for greater parsimony by keeping theoretically independent dimensions from having cross-loadings. There needs to be some focus on why the bi-factor model is theoretically and substantively more relevant as well as providing a better fit. A saturated model, for example, will necessarily fit better than any of the models, but it would provide an appropriate test of the underlying theoretical model or a substantively relevant model. If the theoretical model is a CFA or ESEM factor model, then strong support for a Bi-ESEM reflects a failure of the a priori prediction.

From this perspective, it is important to classify results in relation to the a priori model. Similarly, when comparing nested and non-nested models, the less parsimonious model necessarily fits better for models that do not take into account parsimony. Hence, the size of the difference is relevant, but not necessarily the direction. More interesting are comparisons between non-nested models. These cautionary notes can be useful to avoid over-interpreting goodness-of-fit: even if a Bi-ESEM shows superior fit, it is not necessarily the preferred model which is contingent on theoretical considerations, particularly when bifactor modeling was applied to a single-level rather than a two-level sampling approach (Eid et al., 2017).

Conclusion

This systematic review and meta-analysis aimed to collect and describe studies using a B-ESEM framework in multivariate behavioral research, aggregate their reported model fit, and analyze model fit differences in comparison to reference models and as a function of sample size, item number, and factor number.

This meta-analysis is the first to replicate findings from simulation studies with real data on the superiority of B-ESEM models and examine the relative influence of sample size, item number, and factor number on model fit (Hu and Bentler, 1999; Marsh et al., 2004; Shi et al., 2019). While meta-analyses of structural equation models have been performed (MASEM; e.g., Cheung and Chan, 2005; Reinhold et al., 2018), this meta-analysis is also among the first to synthesize B-ESEM model fit and compare fit between models meta-analytically. This meta-analysis also documented how widespread B-ESEM has been used within the past 6 years since the seminal paper of Morin et al. (2016a) has been published: B-ESEM is now used in multiple domains to explore the multidimensional structure of numerous constructs in educational and psychological research.

Because the review included original empirical reports only—and excluded simulation studies—our examination of the

TABLE 10 Between-Study analysis of the influence of sample size, item number, and specific factor number on model fit.

Model	Sample size				Item number				Number of specific factors			
	<i>n</i>	β	<i>SE</i>	<i>p</i>	<i>n</i>	β	<i>SE</i>	<i>p</i>	<i>n</i>	β	<i>SE</i>	<i>p</i>
One-factor												
χ^2/df	98	0.621	0.080	0.001***	112	-0.022	0.095	0.820	115	0.026	0.094	0.781
CFI	98	-0.126	0.101	0.212	112	-0.492	0.083	0.001***	115	-0.260	0.090	0.005**
TLI	91	-0.144	0.104	0.171	105	-0.491	0.085	0.001***	108	-0.222	0.094	0.021*
RMSEA	97	0.192	0.100	0.058 ^y	111	0.013	0.095	0.889	114	0.120	0.093	0.201
SRMR	50	0.266	0.138	0.060 ^y	59	0.357	0.123	0.005**	59	0.172	0.129	0.188
CFA												
χ^2/df	202	0.397	0.065	0.001***	226	-0.041	0.067	0.541	230	-0.048	0.066	0.471
CFI	228	0.127	0.066	0.055 ^y	251	-0.187	0.062	0.003**	255	0.093	0.062	0.137
TLI	212	0.119	0.068	0.083 ^y	235	-0.160	0.065	0.014*	239	0.123	0.064	0.056 ^y
RMSEA	227	-0.086	0.066	0.194	251	-0.124	0.063	0.049*	255	-0.141	0.062	0.024*
SRMR	93	-0.076	0.104	0.468	107	0.200	0.095	0.038*	107	-0.125	0.096	0.198
ESEM												
χ^2/df	204	0.560	0.058	0.001***	225	-0.095	0.067	0.154	225	-0.122	0.066	0.067 ^y
CFI	228	0.061	0.066	0.361	249	-0.078	0.063	0.218	249	0.251	0.061	0.001***
TLI	217	0.010	0.068	0.883	238	-0.050	0.065	0.441	238	0.114	0.065	0.080 ^y
RMSEA	227	-0.018	0.067	0.786	249	-0.093	0.063	0.142	249	-0.172	0.063	0.007**
SRMR	94	-0.152	0.102	0.142	109	-0.007	0.096	0.938	105	-0.523	0.084	0.001***
H-CFA												
χ^2/df	47	0.540	0.124	0.001***	46	-0.094	0.148	0.531	46	0.055	0.149	0.711
CFI	48	-0.027	0.146	0.854	47	-0.396	0.135	0.005**	47	-0.295	0.141	0.042*
TLI	45	-0.069	0.150	0.650	44	-0.486	0.133	0.001***	44	-0.358	0.142	0.016*
RMSEA	48	-0.143	0.144	0.325	47	-0.292	0.141	0.044*	47	-0.114	0.146	0.439
SRMR	23	0.026	0.213	0.906	24	0.843	0.112	0.001***	22	0.519	0.187	0.011*
H-ESEM												
χ^2/df	20	0.116	0.228	0.617	21	-0.313	0.212	0.157	21	-0.137	0.222	0.544
CFI	20	-0.578	0.187	0.006**	21	-0.488	0.195	0.021*	21	-0.122	0.222	0.588
TLI	19	-0.532	0.200	0.016*	20	-0.381	0.212	0.088 ^y	20	-0.021	0.229	0.928
RMSEA	20	-0.373	0.213	0.096 ^y	21	-0.505	0.193	0.017*	21	-0.445	0.200	0.038*
SRMR	5	-0.298	0.477	0.567	7	0.440	0.367	0.276	7	-0.438	0.367	0.278
B-CFA												

(Continued)

TABLE 10 (Continued)

Model	Sample size			Item number			Number of specific factors					
	n	β	SE	p	n	β	SE	p	n	β	SE	p
χ^2/df	168	0.443	0.069	0.001***	187	-0.143	0.073	0.050 ^y	192	0.093	0.072	0.197
CFI	189	0.012	0.073	0.871	208	-0.455	0.062	0.001***	213	-0.332	0.065	0.001***
TLI	176	-0.026	0.076	0.728	195	-0.408	0.066	0.001***	200	-0.326	0.067	0.001***
RMSEA	188	-0.177	0.072	0.015*	207	-0.012	0.070	0.869	212	0.213	0.067	0.002**
SRMR	67	-0.125	0.122	0.311	80	0.220	0.110	0.049*	81	0.220	0.109	0.047*
B-ESEM												
χ^2/df	238	0.454	0.058	0.001***	258	0.046	0.062	0.458	258	-0.052	0.062	0.408
CFI	267	0.128	0.061	0.036*	287	-0.220	0.058	0.001***	287	0.095	0.059	0.108
TLI	247	0.134	0.063	0.034*	267	-0.300	0.058	0.001***	267	0.025	0.061	0.689
RMSEA	265	-0.048	0.061	0.435	286	0.064	0.059	0.282	286	-0.122	0.059	0.040*
SRMR	104	-0.171	0.097	0.082 ^y	119	0.183	0.090	0.045*	115	-0.298	0.089	0.001***

n, number of studies; β, standardized beta coefficients; SE, standard error.
^yp < 0.10, *p < 0.05, **p < 0.01, ***p < 0.001.

influence of item number and factor number was contingent on and limited to what had been published in original empirical research. Another limitation concerned the domains within which B-ESEM has been applied. Although research in the domains of learning and instruction, motivation and emotion, self and identity, depression and wellbeing, and interpersonal relations covers large areas of educational and psychological research, the findings of this meta-analytic review are limited to these fields and cannot easily be generalized to other domains within which B-ESEM may be applied in the future. Still, we are confident that the present research synthesis—focusing on five fit indices and six reference models, cumulating 158 studies with 308 reports of B-ESEM model fit from a total sample size of 778,624 participants, and examining the relative influence of sample size, item number, and factor number within and between studies—can inform further applications of B-ESEM to identify construct-relevant psychometric multidimensionality. Future research is encouraged to examine how particular constructs and scales in educational and psychological research can be represented with B-ESEM (Morin et al., 2016a).

Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Author contributions

The author confirms being the sole contributor of this work and has approved it for publication.

Conflict of interest

The author declares that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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*Studies preceded by an asterisk were included in the meta-analysis.