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Factor analyses of the Hospital Anxiety and Depression Scale: a Bayesian structural equation modeling approach

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Abstract
Purpose The latent structure of the Hospital Anxiety and Depression Scale (HADS) has caused inconsistent results in the literature. The HADS is frequently analyzed via maximum likelihood confirmatory factor analysis (ML-CFA). However, the overly restrictive assumption of exact zero cross-loadings and residual correlations in ML-CFA can lead to poor model fits and distorted factor structures. This study applied Bayesian structural equation modeling (BSEM) to evaluate the latent structure of the HADS.
Methods Three a priori models, the two-factor, three-factor, and bifactor models, were investigated in a Chinese community sample ($N = 312$) and clinical sample ($N = 198$) using ML-CFA and BSEM. BSEM specified approximate zero cross-loadings and residual correlations through the use of zero-mean, small-variance informative priors. The model comparison was based on the Bayesian information criterion (BIC).
Results Using ML-CFA, none of the three models provided an adequate fit for either sample. The BSEM two-factor model with approximate zero cross-loadings and residual correlations fitted both samples well with the lowest BIC of the three models and displayed a simple and parsimonious factor-loading pattern.
Conclusions The study demonstrated that the two-factor structure fitted the HADS well, suggesting its usefulness in assessing the symptoms of anxiety and depression in clinical practice. BSEM is a sophisticated and flexible statistical technique that better reflects substantive theories and locates the source of model misfit. Future use of BSEM is recommended to evaluate the latent structure of other psychological instruments.

Keywords Hospital Anxiety and Depression Scale (HADS) · Confirmatory factor analysis · Maximum likelihood · Bayesian structural equation modeling · Informative priors

Introduction

The Hospital Anxiety and Depression Scale (HADS), developed by Zigmond and Snaith [1], is widely used for the assessment and screening of anxiety and depression symptoms in clinical and community populations. Previous studies [2, 3] indicated satisfactory levels of internal consistency, concurrent validity, and diagnostic ability for the HADS. However, as a recent systematic review, [4] pointed out that previous findings on the latent structure of the HADS have been largely inconsistent. Although some factor analytic studies [5–7] supported a two-factor structure (anxiety and depression), other studies [8–10] found a superior fit for a three-factor structure. Based on the tripartite theory of anxiety and depression [11], the most commonly supported three-factor structure [9] comprises negative affectivity as an additional factor that accounts for general somatopsychic distress. Nonetheless, the extremely high correlation found between the anxiety and negative affectivity factors [10, 12] casts doubt on the

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differentiability of the two factors and their clinical usefulness as separate constructs. The conflicting findings and apparent discrepancy between studies regarding its underlying dimensionality have given rise to calls for abandoning the HADS [13].

Recently, Norton et al. [14] conducted a meta-analytic confirmatory factor analysis (CFA) on the HADS using data from 28 previous factor analytic studies. They evaluated several a priori factor structures including the innovative bifactor model, which comprises a general distress factor onto which all observed items load and domain-specific anxiety and depression factors onto which observed items with related content load [15]. The bifactor model provided the best fit of all models tested across community and cardiovascular disease samples. Despite the insightful findings on the latent structure of the HADS, several methodological issues are worth noting in this and other CFA studies based on the traditional maximum likelihood (ML) approach.

The first issue relates to inappropriate practice in the evaluation of model fit in ML-based CFA studies. Most of those studies ignored the typically significant result in the χ^2 test of exact fit on the basis of its oversensitivity to trivial discrepancy at large sample sizes. Instead, they relied on approximate fit indices to justify 'approximate' model fit. Nonetheless, despite the high power of the χ^2 test to detect model misfit at large sample sizes, a significant χ^2 does not automatically indicate trivial model misspecification [16–19]. The conventional but questionable practice on the approximate fit indices and arbitrary cut-off criteria was found to contribute little to the determination of the location and severity of the misfit [20]. In fact, researchers have warned against the use of the notorious practice of comparing alternative models based on the difference in approximate fit indices [16–19].

The second issue is the inherent unrealistic model constraints for ML-based CFA. Although cross-loadings and residual correlations between items are presumably fixed at exact zero in typical ML-based CFA, this assumption may not realistically reflect researchers' substantive hypotheses [21]. Unnecessarily strict models with inappropriate exact zero cross-loadings and residual correlations could lead to poor model fit [22] and substantial parameter biases for factor loadings and correlations [23]. Model diagnostic procedures are essential to tracking down the source of misfit and to modify the model accordingly.

Based on the Bayesian structural equation modeling (BSEM) approach [24, 25], Muthén and Asparouhov [21, 26] recently pioneered a new statistical approach in CFA and SEM studies. This specific BSEM approach allows simultaneous estimation of all cross-loadings and residual correlations in a statistically identified model. In particular, approximate zero informative priors are used to replace the exact zeros for the cross-loadings and residual correlations in ML-CFA. Knowledge from previous studies and substantive theory can be incorporated to reflect prior beliefs in the likely parameter values and uncertainty. As BSEM does not rely on large sample normal theory as in the ML approach, it better accommodates skewed distributions of parameter estimates and shows a better small-sample performance [21]. Given its recent emergence and potential for use in factor analysis, this study attempted to apply this BSEM approach to the investigation of the latent structure of the HADS via comparison of the two-factor, three-factor, and bifactor structures.

Methods

Participants and measure

The participants in this study comprised two independent samples of 312 community adults (77.7 % females, mean age = 38.6 years, $SD = 9.9$) and 198 breast cancer patients (100 % females, mean age = 47.8 years, $SD = 7.6$). The two samples were recruited from a mental health rehabilitation complex and four cancer resource centers, respectively, in Hong Kong. Ethical approval was obtained from the local research ethics committee, and written informed consent was obtained from the participants.

The HADS is a 14-item, 4-point self-report Likert scale assessing anxiety and depression symptoms. For the two-factor model proposed by Zigmond and Snaith [1], satisfactory levels of Cronbach's alphas were found for anxiety and depression factors in the community ($\alpha = .83$ and .70) and clinical ($\alpha = .86$ and .76) samples, respectively. Table 1 shows the factor-loading patterns for the two- and three-factor models. All 14 items were standardized for BSEM analysis so that the scale of the priors would correspond to standardized loadings.

Statistical analysis

All statistical analyses were carried out in Mplus 7 [27]. The data and scripts are available from the corresponding author upon request. The respective validities of the two-factor model proposed by Zigmond and Snaith [1], the three-factor model put forward by Dunbar et al. [9], and the bifactor model of Norton et al. [14] were examined in the community and clinical samples using the ML and Bayesian approaches. For the ML approach, CFA was performed with robust maximum likelihood estimator that took into account the items' four-point ordinal response format. All cross-loadings and residual correlations were fixed at exact zero. Model evaluation was based on χ^2 test

Table 1 Factor-loading patterns for the two- and three-factor models for the HADS

Item	Two-factor model		Three-factor model		
	Anxiety	Depression	Anxiety	Negative affectivity	Depression
Tense	X	0	0	X	0
Frightened	X	0	X	0	0
Worrying	X	0	0	X	0
Relaxed	X	0	0	X	0
Butterflies in stomach	X	0	X	0	0
Restless	X	0	0	X	0
Panic	X	0	X	0	0
Enjoyment as usual	0	X	0	0	X
Humor	0	X	0	0	X
Cheerful	0	X	0	0	X
Slowed down	0	X	0	0	X
Disinterest in appearance	0	X	0	0	X
Hope for enjoyment	0	X	0	0	X
Enjoy a good book/TV	0	X	0	0	X

X major factor loadings, *0* cross-loadings. The two-factor model originates from Zigmond and Snaith [1], while the three-factor model is adopted from Dunbar et al. [9]

of exact fit with the comparative fit index (CFI) and root mean square error of approximation (RMSEA) as supplementary fit indices. Missing data were handled through full-information maximum likelihood.

For the BSEM approach, all three a priori models were progressively estimated using a series of priors specification, namely a) exact zero cross-loadings and residual correlations, b) approximate zero cross-loadings and exact zero residual correlations, and c) approximate zero cross-loadings and residual correlations. The approximate zeros were specified using zero-mean, small-variance informative priors which represented a 95 % limit of −.2 to .2 [21]. Model estimation was performed with a default of 10,000 iterations and 50,000 iterations for models with approximate zero residual correlations using the Markov chain Monte Carlo algorithm and the Gibbs sampler [21, 28, 29]. The details of the technical implementation of BSEM are described in Asparouhov and Muthén [28] and Lee and Song [29].

Model convergence was assessed with the potential scale reduction factor (PSRF) diagnostic [30], with a PSRF value of 1.1 or smaller regarded as evidence of convergence. BSEM model fit was assessed with posterior predictive *p* value and the associated 95 % credibility interval [21, 26]. While a low posterior predictive *p* value ($p < .05$) and positive 95 % lower limit point to a poor model fit, a well-fitting model is expected to show a posterior predictive *p* value around .5 and a symmetric 95 % credibility interval centering around zero. Model comparison was based on the Bayesian information criterion (BIC), with smaller values representing better fit [31].

Results

Maximum likelihood analysis

Table 2 reports the ML-CFA results for the three a priori models for the community and clinical samples. For the two-factor model, the correlation between the anxiety and depression factors was .849 and .781 for the community and clinical samples, respectively. For the three-factor model, the correlation between anxiety and negative affectivity was .968 and .965 for the community and clinical samples, respectively. Despite the marginally acceptable approximate fit indices, all three models were rejected by the χ^2 test of exact fit with highly significant results ($p < .01$) for both samples. Given the modest sample sizes, the poor model fit cannot be attributed to the oversensitivity of the χ^2 test to trivial misspecifications at a large sample size. Model diagnostics should be performed to locate the source of model misfit that facilitates the estimation of valid and unbiased models for model comparison.

Bayesian structural equation modeling

Tables 3, 4 present the BSEM results for the three a priori models for the community and clinical samples, respectively. Using the specification of noninformative priors, all three models (Models 1a, 2a, and 3a) displayed a poor model fit for both samples with low posterior predictive *p* values and positive 95 % lower posterior predictive limits. Models 1b, 2b, and 3b, which specified informative priors for the cross-loadings, showed little improvement in

Table 2 Maximum likelihood analysis results for the two-factor, three-factor, and bifactor models for the HADS

Model	χ^2	df	p	RMSEA	CFI
Community sample ($N = 312$)					
Two factor	129.0	76	.000	.047	.940
Three factor	127.5	74	.000	.048	.940
Bifactor	118.3	63	.000	.053	.938
Clinical sample ($N = 198$)					
Two factor	117.5	76	.002	.053	.948
Three factor	116.3	74	.001	.054	.947
Bifactor	177.9	63	.000	.096	.855

CFI comparative fit index, *RMSEA* root mean square error of approximation

the model fit for both samples with low posterior predictive p values and asymmetric 95 % posterior predictive intervals. An exception was that Model 3b provided a marginally acceptable model fit for the clinical sample with a posterior predictive p value of .117 and an asymmetric 95 % posterior predictive interval. Specification of a higher prior variance of .02 or .03 had negligible impact on the model results and posterior predictive p values.

Through specification of informative priors for the cross-loadings and residual correlations, all three models (Models 1c, 2c, and 3c) fitted both samples well with posterior predictive p values around .5 and symmetric 95 % posterior predictive intervals centering at zero. Among the three models, Model 1c had the least amount of free parameters and the lowest BIC for both samples. The substantial differences between Model 1c and the other two models in the BIC (around 94.3 and 86.9 for the community and clinical samples) strongly favor the two-factor structure. The two-factor model solution for both samples is shown in Table 5. It can be seen that the hypothesized major loadings were all recovered at substantial values without any significant cross-loadings. None of the residual correlations, ranging from −.174 to .134 for the community sample and −.141 to .152 for the clinical sample, were statistically significant, and all fell within the prespecified 95 % limit of −.2 to .2. The correlation between the anxiety and depression factors was .646 for both samples.

Discussion

The study evaluated a wide variety of latent structures for the HADS using the traditional ML approach. The results shed some light on the ambiguous findings in previous studies that may have arisen from the analytic methods used. An abundance of ML-CFA studies on the HADS applied unnecessarily strict model constraints in the form of exact zero cross-loadings and residual correlations. This led to frequent model rejection and compelled a sequence of post hoc model modifications that were likely to capitalize on chance [21]. In this study, the omitted residual correlations appear to have been the source of model misfit that potentially contributes to the poor model fit for the ML-CFA models in both samples.

Using BSEM with a series of progressively informative priors, the study demonstrated the evidence for a two-factor structure that tapped into anxiety and depression as originally intended. The findings of this study differ from the conclusion of a recent meta-analytic CFA study by Norton et al. [14], in which the bifactor structure provided the best overall factor solution. There could be two reasons for this discrepancy. First, the Norton et al. study was based on the

Table 3 Bayesian structural equation modeling results for the HADS for the community sample ($N = 312$)

Model	Priors specification	No. of free parameters	2.5 % PP limit	97.5 % PP limit	PP p	BIC
Two-factor structure						
1a	Noninformative	43	38.9	109.1	.000	11,454.2
1b	Informative (cross-loadings)	57	21.3	100.2	.001	11,518.7
1c	Informative (cross-loadings + residual correlations)	148	−45.0	41.4	.521	11,907.0
Three-factor structure						
2a	Noninformative	45	36.1	109.6	.000	11,463.1
2b	Informative (cross-loadings)	73	19.3	94.1	.003	11,604.9
2c	Informative (cross-loadings + residual correlations)	164	−44.5	43.5	.516	12,001.3
Bifactor structure						
3a	Noninformative	56	10.7	86.8	.006	11,511.0
3b	Informative (cross-loadings)	70	−6.9	74.5	.042	11,581.5
3c	Informative (cross-loadings + residual correlations)	161	−43.9	42.0	.516	12,010.2

PP posterior predictive, *BIC* Bayesian information criterion; informative priors on cross-loadings and residual correlations have a zero mean and a variance of .01

Table 4 Bayesian structural equation modeling results for the HADS for the clinical sample ($N = 198$)

Model	Priors specification	No. of free parameters	2.5 % PP limit	97.5 % PP limit	PP p	BIC
Two-factor structure						
1a	Noninformative	43	20.7	94.3	.001	7,153.1
1b	Informative (cross-loadings)	57	9.7	84.2	.007	7,212.7
1c	Informative (cross-loadings + residual correlations)	148	−45.3	42.4	.540	7,575.7
Three-factor structure						
2a	Noninformative	45	20.4	94.2	.004	7,161.5
2b	Informative (cross-loadings)	73	10.4	85.3	.006	7,292.5
2c	Informative (cross-loadings + residual correlations)	164	−45.8	41.6	.543	7,662.6
Bifactor structure						
3a	Noninformative	56	5.3	71.5	.039	7,186.4
3b	Informative (cross-loadings)	70	−14.5	63.5	.117	7,252.6
3c	Informative (cross-loadings + residual correlations)	161	−45.0	41.2	.543	7,662.6

PP posterior predictive, *BIC* Bayesian information criterion; informative priors on cross-loadings and residual correlations have a zero mean and a variance of .01

Table 5 BSEM two-factor model solution using informative priors for cross-loadings and residual correlations (Model 1c) for the HADS

Item	Community ($N = 312$)		Clinical ($N = 198$)	
	Anxiety	Depression	Anxiety	Depression
Feel tense or wound up	**.720***	−.022	**.780***	−.048
Frightened feeling	**.727***	−.012	**.746***	−.010
Worrying thoughts	**.615***	.043	**.731***	.046
At east and feel relaxed	**.610***	.056	**.645***	.068
Butterflies in the stomach	**.675***	.005	**.752***	.004
Feel restless	**.607***	−.026	**.640***	−.014
Sudden feelings of panic	**.693***	.014	**.794***	.013
Enjoy the things used to enjoy	−.010	**.536***	−.012	**.512***
See funny side of things	−.002	**.545***	−.006	**.621***
Feel cheerful	.003	**.638***	.032	**.697***
Slowed down	.056	**.508***	.058	**.612***
Lost interest in appearance	−.004	**.514***	−.026	**.574***
Look forward with enjoyment	−.003	**.670***	.011	**.724***
Enjoy a good book/radio/TV	.037	**.480***	−.002	**.645***
Factor correlation	.646*		.646*	

Bolded values indicate the major loadings. Statistically significant cross-loadings (marked with asterisks) have a 95 % credibility interval that does not cover zero

traditional ML approach and did not obtain exact chi-square fit for the bifactor model. Despite the large size of their sample, the failure to track down and account for the model misfit may have led to biased results. Second, their study adopted the questionable practice of using difference in approximate fit indices for model comparison. The bifactor model was identified as the best model with the lowest BIC in only 8 (28.6 %) of the 28 studies.

In the present Bayesian analyses, the bifactor model with approximate zero cross-loadings failed to provide an adequate fit to the community and clinical samples. Although the addition of approximate zero residual correlations resulted in a well-fitting bifactor model, this model had a substantially higher BIC than that of the two-factor model. Given that the BIC penalizes model complexity, apparently the number of additional parameters estimated for the bifactor model was not offset by the improvement in model fit, suggesting that the bifactor model may overfit the data.

However, the two-factor structure with approximate zero cross-loadings and residual correlations credibly fitted both samples well and showed the lowest BIC among its counterparts. While high inter-factor correlations were observed in the Norton et al. study ($r = .73$–$.80$) [14] and the ML analysis in this study ($r = .78$–$.85$), the correlation in Model 1c was not excessively high ($r = .646$) in either sample. The moderately large magnitude of the correlation plausibly reflects the common comorbidity of anxiety and depression and the overlap of their symptoms [32].

BSEM specifies approximate zeros for the model parameters by allowing slight deviation from the theoretically hypothesized zeros. The analytic approach of specifying approximate zero residual correlations is to some extent analogical to recent practice of including an item wording method factor to improve the model fit [33, 34]. In this study, via the use of informative priors, the cross-loadings and residual correlations were shrunk toward their zero prior mean and were within the prespecified 95 % limits of −.20 to .20, indicating a simple and parsimonious factor-loading pattern. Theoretical knowledge and findings from previous studies can be incorporated into the informative priors to better reflect the hypothesized degree of precision and substantive theories on the factor model. This technique allows simultaneous estimation of all cross-loadings and residual correlations that would not have been feasible in the conventional ML approach because of the model nonidentification issue. The source of model misfit can also be detected systematically via the BSEM approach.

In summary, this is the first study to apply the flexible and innovative BSEM approach to evaluate various factor structures, including the new bifactor structure, for the HADS. The results demonstrate a well-fitting and concise two-factor structure that cross-validates two independent samples. The use of HADS subscale scores is recommended to assess symptoms of anxiety and depression in clinical practice. The two-factor structure with approximate zero cross-loadings and residual correlations should be considered in future psychometric research on the HADS. Given the infrequent use of Bayesian methodology in psychometric research and the increasing ease of access to BSEM [27], future studies should apply the method to evaluate the latent structure of psychological instruments.

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