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A Systematic Review and Meta-Analytic Factor Analysis of the Depression Anxiety Stress Scales

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Abstract

Despite the increasingly widespread usage of the Depression Anxiety Stress Scales (DASS), its latent factor structure has yet to be reviewed. We thus carried out a systematic review of studies examining the latent factor structure of the DASS, further synthesizing findings by performing meta-analytic factor analyses on the available data from said studies. The literature search was conducted across three databases, yielding 59 articles encompassing 89 factor analyses. Reviewed results varied across factor analytic approaches (EFA vs. CFA) and DASS versions (DASS42 vs. DASS21), though the original 3-factor structure of the DASS was generally supported. However, bifactor models (consisting of a general factor and group factors) were most consistently best-fitting whenever tested, supporting an underlying unidimensional construct in DASS. This notion was corroborated by our meta-analytic factor analyses, wherein DASS21 bifactor models demonstrated the same consistent performance, though DASS42 analyses were inconclusive between a 3-factor and 1-factor solution. Our findings fit in with broader historical and contemporary developments in the field, and reinforce the potential utility of bifactor models in illustrating the overlap between depression and anxiety. Some recommendations moving forward are discussed.

Keywords: depression; anxiety; Depression Anxiety Stress Scales; factor structure; meta-analytic factor analysis

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The current research work systematically reviews and analyzes findings from studies which have investigated the factor structure of the widely used Depression Anxiety Stress Scales, a questionnaire purposed to be able to distinguish the three constructs of depression, anxiety and stress. Our findings provide support for the notion of a strong general element of psychopathology underlying the three, in line with previous discussions and upcoming developments in the field.

A Systematic Review and Meta-Analytic Factor Analysis of the Depression Anxiety Stress Scales

Although Depression and Anxiety are two of the most commonly occurring and widely recognized disorder syndromes (American Psychiatric Association, 2013; Demyttenaere et al., 2004; World Health Organization, 2017), it has always been difficult to separate them empirically. Indeed, a plethora of studies has consistently documented substantial overlap between the two, across various populations and modes of assessment (e.g. Breier, Charney, & Heninger, 1985; Brown et al., 2001; Gotlib, 1984; Mineka, Watson, & Clark, 1998; Moffitt et al., 2007; Spinhoven, van Balkom, & Nolen, 2011; Tanaka-Matsumi & Kameoka, 1986; Zuckerman et al., 1967; Zurawski & Smith, 1987). This overlap affects researchers and practitioners alike (Zhiguo & Yiru, 2014), and is recognized to be a persistent challenge in the field.

With this in mind, researchers have attempted to create assessment instruments which provide maximum discriminability between the two syndromes. Of particular note here is the Hospital Anxiety and Depression Scale (HADS; Zigmond & Snaith, 1983), an instrument used prolifically in medical settings to assess anxiety and depression in non-psychiatric outpatients. However, a recent systematic review (Cosco et al., 2012) drew into question the robustness of the scale's bidimensional structure – which was originally proposed to reflect anxiety and depression respectively – instead suggesting that the scale be used as a more general measure of emotional distress given the observed inconsistent delineations of its two subscales.

In light of such findings, it would be interesting and informative to consider the factor structure of another similarly purposed scale which is likewise widely used, namely the Depression Anxiety Stress Scales (DASS).

The Depression Anxiety Stress Scales (DASS)

The Depression Anxiety Stress Scales (DASS) was created by Lovibond and Lovibond (1995a) over the period of 1979-1990, with the goal of conceiving scales that would cover the full range of core symptoms of depression and anxiety. As with the HADS, a key objective of developing the DASS was to provide maximum differentiation between the two syndromes. However, while the HADS did not involve latent variable analyses in its creation (Cosco et al., 2012), the DASS was developed via utilization of an empirically driven bootstrapping strategy, which was considered rather unique at the time. Its factors were initially conceptualized according to clinical consensus, but were subsequently refined using statistical methods such as confirmatory factor analysis and multiple-group factor analysis. Testing was conducted across 30 samples, with items being iteratively added or removed between successive tests. Although the focus of the DASS was originally only concerned with depression and anxiety, this empirical procedure led to the emergence of a third factor comprised of non-discriminating symptoms of the two syndromes. Lovibond and Lovibond observed that these items seemed to reflect some form of general tension (e.g. irritability, agitation), and thus labelled this subscale “Stress”. Of note, the essential stages of scale development were conducted with data from non-clinical individuals, underscoring another key aim of DASS to serve as a measure of general affective syndromes in the wider population.

The resultant DASS consisted of 42 items evenly spread across the subscales of Depression, Anxiety, and Stress (Lovibond & Lovibond, 1995a). Within each subscale, Lovibond and Lovibond had also proposed subcategories consisting of 2-6 items each, describing facets of their respective syndromes (see Lovibond & Lovibond, 1995b). Due however to the purely rational rather than empirical allocation of items to subcategories, they recommended that these subcategories merely be used as descriptors for grouping items together,

1 or for further research purposes. As such, the DASS subscale scores are meant to represent
2 individuals' general affective states (or traits) on the broad syndromes of depression, anxiety and
3 stress, based on a dimensional rather than categorical conception of the three. Notably, while the
4 authors concluded that the DASS was indeed able to successfully discriminate between these
5 three emotional syndromes, they nonetheless still observed moderate to high correlations
6 between its three subscales (ranging from 0.54 to 0.65, Lovibond & Lovibond, 1995b).

7 The DASS has seen widespread usage since its creation, which is likely in part due to it
8 being freely available for use. Along with the later-developed shortened version of the DASS
9 with 21 items (DASS21), it has been used within numerous research contexts such as assessing
10 symptoms or validating other measures, with both versions typically displaying good
11 psychometric qualities such as internal consistency and temporal stability (e.g. Antony et al.,
12 1998). To the best of our knowledge however, a systematic review of studies examining the
13 latent factor structure of the DASS has yet to be conducted despite the increasing popularity of
14 the scale and the accumulation of its psychometric investigations over the last two or so decades.

15 The need to conduct such a review goes in hand with additional considerations brought
16 about by developments in the field. In the years following the conceptualization of the DASS,
17 researchers have increasingly considered more complex hierarchical organizations when trying
18 to model psychopathology. For instance, *higher-order* models afford a way to explain the
19 correlations among lower-order factors via one or more higher-order factors (Chen, West, &
20 Sousa, 2006). Similarly, the *bifactor* approach models scale items as being explained by both a
21 common general factor as well as an orthogonal group factor (Reise, 2012). Despite their
22 statistical differences, both methodologies share the same overarching goal of trying to elucidate
23 a common facet underlying certain components, which is particularly useful in our case in trying

to investigate generalities underlying symptoms and syndromes. Attempts to model depression and anxiety using both approaches have garnered promising findings (e.g., Burns & Eidelson, 1998; Iani, Lauriola, & Costantini, 2014; Simms et al., 2008). Moreover, given the recent developments in meta-analytic factor analysis techniques (see Gnambs & Staufenbiel, 2016), researchers are now able to quantitatively synthesize previous factor analytic findings and perform their own analyses on them (e.g. Norton et al., 2013). This has also yet to be attempted on the DASS.

Thus, the purpose of the current study is twofold. First and foremost, we aim to examine the factor structure of the DASS, by systematically reviewing studies which have performed latent factor analysis on the scale. Secondly, we will also conduct our own meta-analytic factor analysis using the available data from said studies, as an attempt to quantitatively synthesize previous findings.

Method

Search Strategy and Screening

The systematic literature search was conducted across the databases of PsycInfo, Pubmed and Web of Science, with the time frame set as 1st January 1993 (encompassing the conception of the DASS) to 1st March 2018. Keywords related to both the DASS and psychometric analyses were entered into the search commands: regarding the DASS, the terms “depression anxiety stress scales” and “dass” were entered with the Boolean operator “OR”, and psychometric terms consisting of “valid*”, “psychometric”, “factor”, “structure”, “eval*” and “assess*” were similarly entered with the “OR” operator. The two subsets of terms were then aggregated using the Boolean operator “AND”. For instance, the full search string for the PsycINFO database was: ALL(((“depression anxiety stress scales” OR dass) AND (valid* OR psychometric OR factor OR

structure OR eval* OR assess*))). The search results of each database were screened in two stages. At both stages, two raters screened each entry independently and discussed when discrepancies arose.

After the initial exclusion of duplicate entries, entries were screened according to the following three criteria: 1) The paper must have been published in English, 2) The paper must have been an empirical study published as a full journal article (additionally excluding dissertations, reviews, books, case studies, conference abstracts, etc.) and 3) the DASS must have actually been utilized. At this first stage, records were primarily screened based on the title and abstract, further taking a quick skim of the methods section wherever necessary.

Following this, entries were screened for final inclusion according to the criterion that they must have involved some form of latent factor analysis (e.g., exploratory factor analysis or confirmatory factor analysis) on the full scale of DASS42 or DASS21 (i.e., not just on its constituent subscales). At this stage, the main texts of the articles were examined.

Data Extraction

Following screening, all included articles were downloaded for data extraction, which was carried out by two independent coders. The coders determined which version of the DASS was used (DASS42, DASS21, both, or with other variants), as well as the factor analytic approach employed (exploratory factor analysis [EFA], confirmatory factor analysis [CFA], both, or other analyses). The studies were then separated into categories with some studies overlapping across classifications based on them having run multiple analyses.

Data relating to the study characteristics were extracted, namely the number of subjects involved, the population(s) sampled, the country (or countries) they were sampled from, and the language of the DASS employed. Methodological details were also extracted. For EFA studies,

these consisted of the factor extraction method used, nature of rotation, and criteria for determining the number of factors to retain. For CFA studies, data were extracted pertaining to the estimation method used, and the model testing approach—whether more than one model was tested, and whether models other than the ‘standard’ three-factor structure were tested. The phrase ‘standard three-factor structure’ refers here not only to the original DASS structure, but also encompasses variants of it with minor modifications such as correlated items/cross-loadings/shortened subscales/collapsed category responses. On the other hand, ‘other’ models refer here to one-factor solutions, two-factor solutions, models with three-factors but with conceptually redefined subscales, second-order models, and bifactor models.

Regarding analysis results, for EFAs, the final extracted structure was noted, along with any cross-loaded items, which we defined as items with a factor loading of $>.4$ on more than one factor, as well as any differentially loaded items, which we defined as items with a loading of $>.4$ that loaded higher on a different factor than in the original target factor. As for CFAs, the best-fitting factor structure was identified, along with its corresponding fit statistics—the comparative fit index (CFI) and root mean square error of approximation (RMSEA).

Finally, analyses that solely utilized the methods of pooled CFA (i.e., combining the DASS items with items from other scales) or multigroup CFA (i.e., examining measurement invariance) were excluded. Analyses were also excluded if they did not report sufficient details to ascertain a best-fitting structure.

Meta-Analytic Factor Analyses

We first performed meta-analytic EFA on the DASS21, following Shafer’s approach (2005; also see Frick et al., 1993; Loeber & Schmalzing, 1985). Factor structure information was extracted from available EFA data to construct a co-occurrence matrix reflecting the number of

1 times each item loaded saliently (above a loading of .4) on the same subscale as every other item,
2 across all samples. EFA was conducted on the resultant co-occurrence matrix. Velicer's
3 Minimum Average Partial (Velicer, 1976; Zwick & Velicer, 1986) was used to determine the
4 number of factors to be retained. Factors were then extracted using the generalized weighted
5 least squares method with Crawford-Ferguson Parsimax rotation (Crawford & Ferguson, 1970).
6 We also explored bifactor structures by using two approaches, namely the Jennrich-Bentler
7 (Jennrich & Bentler, 2011) rotation and the Schmid-Leiman (Schmid & Leiman, 1957)
8 transformation.

9 Despite the advantages of the aforementioned meta-analytic EFA approach (see Gnambs
10 and Staufenbiel, 2016), it does not account for the strength of the actual factor loadings nor the
11 rotational methods originally used. As such, we further ran meta-analytic CFA using the two-
12 stage structural equation modeling (TSSEM) approach proposed by Cheung and Chan (2005,
13 2009). A pooled correlation matrix was estimated in the first stage of TSSEM—data were
14 extracted from studies which either reported their raw item-level correlation matrices, or reported
15 both full factor loadings and inter-factor correlations which allowed us to compute their implied
16 correlation matrices. At this stage, data from both EFA and CFA studies were used, as long as
17 the aforementioned required components were available. A fixed-effects model was used to
18 combine correlation matrices due to there being an insufficient number of matrices available to
19 estimate a random-effects one. The second stage of TSSEM involved fitting CFA models to the
20 pooled correlation matrix using a weighted least squares estimator with the asymptotic
21 covariance matrix as the weight matrix. We compared factor models identified in the systematic
22 review, based on root mean square error of approximation (RMSEA), standardized root mean
23 square residual (SRMR), comparative fit index (CFI), Tucker-Lewis index (TLI), Akaike

information criterion (AIC) and Bayesian information criterion (BIC). DASS42 models were fitted using the data available from the DASS42 studies, whereas DASS21 models were fitted using the data available from both DASS42 studies and DASS21 studies.

All statistical analyses were performed in R (R Core Team, 2018), using the psych (Revelle, 2018), GPArotation (Bernaards & Jennrich, 2005), OpenMx (Neale et al., 2016) and metaSEM (Cheung, 2015) packages.

Results

Literature Search and Final Inclusion

The literature search identified 2647 studies, from which 1201 met the first set of inclusion criteria. Following the second round of screening, 70 articles were identified to involve latent factor analysis on the DASS. One article was excluded as its full version could not be obtained. Inter-rater reliability across these two rounds was high, at 96%.

Upon further applying our final exclusion criteria as described in the Method section, we excluded eight articles. We additionally decided to exclude analyses utilizing Rasch analysis and Item Response Theory due to their low number, which led to a further exclusion of two articles. Ultimately, this left us with a final set of 59 unique articles, encompassing a total of 86 factor analyses (see Fig. 1). The list of included articles can be found in the supplementary material.

Figure 1. Literature screening summary (article numbers)

Additionally, details of the extracted sample and analysis characteristics, as well as full summaries of models tested and best-fitting models, can be found in supplementary tables 1-6.

Exploratory Factor Analysis Studies

DASS42 EFAs.

We identified a 11 EFAs conducted on the DASS42. Six of these were run on clinical/subclinical participants, four on non-clinical participants, with one analysis not clearly specifying its sample characteristics. Five analyses utilized the English version of the DASS42, and six utilized translated versions. A summary of the best-fitting models is presented in supplementary table 5, left column (and best-fitting model totals split by DASS language and sample clinical status are additionally presented in supplementary tables 7 and 9 respectively). On the surface, there appeared to be predominant support for the standard 3-factor structure of DASS. However, more than half of the analyses either pre-specified the extraction of three factors or did not state their factor retention criteria, and therefore their findings did not inform

us whether the standard 3-factor structure was comparatively the best. Of the remaining analyses which extracted factors using conventional factor retention criteria (e.g., Kaiser rule, Scree plot, etc.), the 3-factor model was still clearly the most frequently best-fitting. Notably, there were anomalous factor loadings present in nearly all of the best-fitting 3-factor models.

DASS21 EFAs.

We identified 17 EFAs conducted on the DASS21. Five of these were run on clinical/subclinical participants, 11 on non-clinical participants, and one on a mixed sample. Eight analyses utilized the English version of the DASS21, eight utilized translated versions, and one included a mix of different language versions. The results pertaining to best-fit are summarized in supplementary table 5, right column (and best-fitting model totals split by DASS language and sample clinical status are additionally presented in supplementary tables 7 and 9 respectively). Unlike the DASS42 EFAs, evidence for the 3-factor structure was mixed. Of the 14 analyses which reported using conventional factor retention criteria, only five found support for the 3-factor structure. Moreover, anomalous factor loadings were again present in nearly all the best-fitting 3-factor models. Interestingly, there was some support for both a 1-factor model and 4-factor models of the DASS21 in these analyses.

General observations.

Some additional observations can be made pertaining to the methodologies used in these EFA studies. Of the 28 EFAs that were run on the DASS42 or DASS21, the most commonly reported factor extraction method used was Principal Component Analysis (PCA) (16 analyses), followed by Principal Axis Factoring (7 analyses) (see supplementary tables 1 and 2 for a full list of the methods used). It should be noted that PCA is arguably not recommended for factor extraction (Widaman, 1993), despite its popular usage observed here.

Moreover, of the 24 analyses which extracted a multi-factor structure, orthogonal rotation was exclusively used in eight analyses. This approach is questionable—even though the DASS was designed to provide maximum discriminability between the syndromes, it is still likely that its subscales will have moderate to high correlations given the documented comorbidity between depression and anxiety. As such, it is more realistically appropriate to rotate factors using an oblique method, as was done in the original DASS as well (Lovibond and Lovibond, 1995b).

Confirmatory Factor Analysis Studies

DASS42 CFAs.

Fifteen DASS42 CFAs were identified, of which six involved clinical/subclinical samples and nine non-clinical. Ten analyses utilized the English version of the DASS42, and five utilized translated versions. The best-fitting models are summarized in supplementary table 6, left column (and best-fitting model totals split by DASS language and sample clinical status are additionally presented in supplementary tables 8 and 10 respectively). The standard 3-factor model was the most frequent best-fitting model (even after disregarding analyses which did not test alternative models). However, correlated errors and/or permitted cross-loadings were prevalent in nearly all these models, though the veracity of their usage in improving model fit remains debatable (Gerbing & Anderson, 1984). Both 1-factor and ‘standard’ 2-factor models (created by retaining the items in each subscale, but combining two of the subscales into a single factor) were also commonly tested, though they were not best-fitting in any analyses. Additionally, two analyses tested bifactor models against the 3-factor solution and 1-factor solution, finding the bifactor model to have better fit in both instances.

DASS21 CFAs.

Forty-three DASS21 CFAs were identified. Of these, seven were conducted on clinical/subclinical participants, 34 on non-clinical participants, and two on mixed samples. Twenty-eight analyses utilized the English version of the DASS21, 14 utilized translated versions, and one analysis used a mix of different language versions. The best-fitting models are summarized in supplementary table 6, right column (and best-fitting model totals split by DASS language and sample clinical status are additionally presented in supplementary tables 8 and 10 respectively). In these analyses, support for the standard 3-factor structure of the DASS was mixed. In analyses where alternative models were tested against the original 3-factor solution, it had best-fit (or tied for best-fit with a second-order model) only in 10 out of 27 analyses. The usage of correlated errors in the best-fitting 3-factor solutions overall was lower than among DASS42 CFAs. Notably, both 1-factor and ‘standard’ 2-factor models were also commonly tested (particularly the former), though again they were not found to be best-fitting in any of the analyses.

The mixed support for the standard 3-factor solution of DASS21 could be due to the increased prevalence of including bifactor models in the analyses. If we only consider analyses which tested the 3-factor model against alternative models not including bifactor structures, the 3-factor solution fit best—or tied for best fit—in nine out of 11 occasions. Conversely, of the analyses which tested the 3-factor model against bifactor models, all but one (Johnson et al., 2016) found a bifactor solution to be best-fitting.

Of all the best-fitting bifactor structures, 11 of them fit best to a structure with one general distress factor and three group factors, whereas four fit best to a structure with one general distress factor and two group factors (namely Depression and Anxiety, with Stress items only being allowed to load onto the general factor). These two alternative bifactor structures

were only directly compared in eight of these analyses, with the former fitting better in six. All in all, there was convergent evidence for the potential applicability of a bifactor structure to the DASS.

Additionally, seven analyses tested factor solutions with the DASS items shifted around to create conceptually redefined first-order factors, in attempts to more explicitly reflect components of the influential Tripartite theory of Anxiety and Depression put forth by Clark and Watson (1991). Said theory proposed that symptoms of anxiety and depression can be categorized into a shared factor and unique factors for each syndrome, with the shared factor reflecting general distress or general negative affect which is common to both syndromes, and the unique factors reflecting somatic/physiological hyperarousal and anhedonia/loss of interest which are specific to anxiety and depression respectively. However, only two of these analyses found such ‘Tripartite’ solutions to be best fitting. One analysis (Clara, Cox, & Enns, 2001) selected items from the DASS originally designated by Lovibond and Lovibond (1995b) to reflect Anhedonia/Low Interest (relating to depression), Physiological Arousal (relating to anxiety), and being Easily Upset or Irritable (reflecting general distress). This 15-item 3-factor Tripartite solution had better fit than the standard 3-factor structures of both DASS21 and DASS42. Another study (Duffy, Cunningham, & Moore, 2005) alternatively conceived Tripartite factors by selecting four items to represent Physiological Arousal, four items for lack of Positive Affect, and the remaining items of the DASS21 to represent Generalized Negativity. Though this model had poor fit, the authors combined the two factors of Positive Affect and Generalized Negativity to create a two-factor solution which fit better than the standard 3-factor model. However, this solution failed to achieve best fit in subsequent analyses.

General observations.

Pertaining to the most frequently used estimation methods in these 58 CFAs, 11 used Maximum Likelihood, 11 used Robust Maximum Likelihood, 19 used Weighted Least Squares (with means and variances adjusted), and two used Bayesian or Unweighted Least Squares. The estimation method was not specified in 15 analyses. It should be noted that Maximum Likelihood estimator requires the assumption of normality, which can only be achieved with continuous variables, or arguably by approximating Likert (i.e., ordinal) scales with at least five response categories (Rhemtulla, Brosseau-Liard & Savalei, 2012). The DASS items are scored on a 4-point scale, and therefore require methods meant for ordinal variables, in which case the Weighted Least Squares method is currently the preferred option (Rhemtulla, et al., 2012). However, this method estimates latent variable correlations through analyzing the bivariate contingency tables of item responses, and thus requires a relatively large sample to avoid empty cells in these contingency tables (for more on this topic see Li, 2016; and Rhemtulla et al., 2012).

Meta-Analytic Factor Analyses

Meta-analytic exploratory factor analysis.

Eighteen EFA studies on either DASS42 or DASS21 reported sufficient information to be included in the construction of co-occurrence matrix for DASS21. The 3-factor solution was selected based on Velicer's MAP statistic (supplementary table 11), and factors were rotated using the Crawford-Ferguson Parsimax criterion. The resultant factor structure was one that closely matched the original DASS21 3-factor oblique model, with each item loading saliently ($>.4$ loading) on its respective factor (table 1). Interfactor correlations were present but not large, suggesting adequate separation of factors.

Two bifactor EFA methods were additionally applied. Using the Jennrich-Bentler rotation, the Depression and Stress subscales of the DASS were largely retained as two group

factors of the model, though over half of the Anxiety items no longer loaded saliently on a group factor. Conversely, the Schmid-Leiman transformation produced a parsimonious model wherein each item loaded saliently on both the general factor and a group factor, with the group factors maintaining the original structure of the DASS21 (table 1).

Meta-analytic confirmatory factor analysis.

Twenty-four studies with sufficient information were included in this analysis, encompassing 30 unique samples. Supplementary table 12 presents a summary of all tested models and fit statistics. When DASS21 models were fitted using all the available data, a bifactor model with one general distress factor and three group factors (of Depression, Anxiety and Stress) consistently fit the data best across all the subsample analyses (table 2; supplementary table 12). Further examination of the factor loadings from this best-fitting model (table 3) revealed that items loaded more heavily on the general factor than the group factors, suggesting that the general factor explained a large proportion of the variance. This was indicated in the consistently high item-level explained common variance (I-ECV). The overall explained common variance (ECV) was .97, indicating that 97% of variance in all the items was being explained by the general factor. This extremely high ECV provided strong support for a unidimensional construct underlying DASS21.

On the other hand, results of the analyses using only the DASS42 samples were not as clear (table 2). The BIC, RMSEA and TLI statistics favored a 3-factor model, whereas CFI, SRMR and AIC favored a bifactor model with one general distress factor and two group factors (of Depression and Anxiety, with Stress items only being allowed to load on the general factor). Different results between the analyses on DASS21 and on DASS42 could either be due to differences in characteristics of these DASS42 samples, or due to actual differing psychometric

qualities between the DASS21 and DASS42. Therefore, additional analyses testing DASS21 models were conducted on the same subgroup of DASS42 samples to explore the first possibility. Results from these new analyses clearly favored a bifactor model with one general factor and three specific factors (of Depression, Anxiety and Stress), congruent with the above described analyses on DASS21. Moreover, an examination of the aforementioned best-fitting DASS42 3-factor structure loadings (supplementary table 13) revealed that the interfactor correlations between the three subscales were all essentially 1.00. In light of these perfect interfactor correlations, we additionally fitted a post-hoc DASS42 1-factor model (see table 2), finding it to have near identical fit to said DASS42 3-factor model. This may indicate that the three factors were statistically indistinguishable from each other, or may reflect computational issues in model estimation. Similar meta-analyses involving more samples are needed to elucidate this. In any case, our results from DASS42 analyses also seem to converge on a strong common factor underlying all items.

Discussion

The current study systematically reviews studies examining the latent factor structure of the Depression Anxiety Stress Scales (DASS), a popular scale widely used to measure depression and anxiety. The review involved 59 extracted articles encompassing 86 analyses. Findings are further augmented by meta-analytic factor analyses which synthesize the available data from included studies.

Pertaining to the reviewed evidence from EFAs, findings differed across the two versions of the DASS. Support for the 3-factor structure was more consistent in the DASS42, but mixed in the DASS21. One possible reason for this discrepancy could be that the extra items in DASS42 may have helped to further delineate the three DASS constructs, implying that the full

DASS may be more practical preferable in situations wherein its subscales need to be considered separately. However, this notion must be taken with caution due to the small sample of analyses examined here, and also because it does not appear to be fully supported by our meta-analytic CFAs (as discussed below).

As for the reviewed CFA studies, there again appeared to be more consistent support for the 3-factor model in DASS42 analyses. However, this seemed primarily due to the differences in alternative models tested in analyses of the two DASS versions, with bifactor solutions being tested more frequently in DASS21 analyses. Indeed, the standard 3-factor structure was clearly the most frequently best-fitting model across both versions in analyses wherein bifactor solutions were *not* considered, having better model fit than alternative first-order models consistently. As for the redefined ‘Tripartite’ factor structures that were tested, their poor performance may simply have been due to the DASS not containing enough items to adequately model the Tripartite components (in particular the syndrome-specific factors of Anhedonia and Physiological Hyperarousal), whereas work utilizing a scale which was specifically designed to measure said constructs (namely the Mood and Anxiety Symptom Questionnaire by Watson & Clark, 1991) has demonstrated better differentiation of its elements (e.g. Keogh & Reidy, 2000; Wardenaar et al., 2010). In any case, the consistent good fit of the standard 3-factor model of the DASS in the currently reviewed CFAs—though slightly contradicting implications from the aforementioned EFA analyses—nonetheless encouragingly attests to the robustness of the original 3-factor structure of the DASS, at least where only first-order models are considered.

Following that note, it is particularly interesting to consider hierarchical models of the DASS, given the increasing attempts in the literature to conceptualize anxiety and depression as being subsumed under some form of higher-order framework (e.g. Brown et al., 1998; Mineka et

al., 1998). One potential method to model this hierarchical organization is via the use of second-order factor models, though said models had poor performance relative to bifactor solutions in our sample of analyses, being worse-fitting than bifactor models on all three occasions wherein they were tested against each other. Surprisingly, there were also several instances in which a second-order model—with one second-order factor upon which the three first-order factors of the DASS loaded—had different fit indices to the standard 3-factor correlated model (with no correlated errors or permitted cross-loadings). This is strange given that these two models should be mathematically equivalent (Chen et al., 2006).

As such, a better approach to examine the contributions of a hierarchical element subsuming anxiety and depression in DASS may be via bifactor modeling, as supported by our current review. Of the 17 CFAs which tested a bifactor solution against alternative models (all of which included the standard 3-factor solution of the DASS), all but one found it to be the best-fitting model. Questions do remain regarding the optimal bifactor structure, namely whether the DASS is best modeled by a bifactor solution with one general factor and three group factors (of Depression, Anxiety and Stress) or a bifactor solution with one general factor and two group factors (of Depression and Anxiety, with Stress items only being allowed to load on the general factor). Our current review found more support for the former thus far. This in turn questions the true nature of the DASS Stress subscale, and whether or not it constitutes its own independent construct as maintained by the creators of the DASS (Lovibond, 1998; Psychology Foundation of Australia, 2014), or whether it merely reflects the general factor underlying Depression and Anxiety. More research is needed to elucidate this, though the applicability of the bifactor structure in modeling depression and anxiety certainly proves to be a promising starting point.

1 These findings are also consistent with previous research applying such approaches in different
2 scales of depression and anxiety (e.g. Iani et al., 2014; Simms et al., 2008).

3 Our review is not without limitations, perhaps most notably being that we did not involve
4 data from unpublished analyses. As such, the current review may be biased against possible
5 analyses which failed to fit the DASS to any factor solution whatsoever. However, we do believe
6 that the publication bias for research of this nature may not be that substantial, as poor model fit
7 may not necessarily preclude a latent factor analytic study from being published, unlike studies
8 which adopt a conventional hypothesis testing approach to investigate a psychological
9 phenomenon.

10 The findings from our systematic review were further generally corroborated by meta-
11 analytic factor analyses conducted using the available data. Firstly, meta-analytic EFA conducted
12 on the co-occurrence matrix revealed the originally proposed 3-factor structure of the DASS21.
13 A bifactor solution comprising one general factor and three group factors also emerged. The
14 limitations of the approach employed here must however be reiterated—said analyses were run
15 on a co-occurrence matrix and thus did not take into account the strength of factor loadings or
16 interfactor correlations. As such, the final extracted factor structures primarily reflect the
17 commonly identified factor structures in the included samples, and it is difficult to make
18 arguments regarding optimal structure with these analyses alone.

19 In this light, findings from our meta-analytic CFAs were more informative, as they
20 allowed us to compare models while also accounting for the strength of factor loadings. DASS21
21 models fitted using available data from both DASS42 and DASS21 samples consistently found a
22 bifactor model with one general factor and three group factors of Depression, Anxiety and Stress
23 to fit the data best. This was the case even in sub-analyses conducted (based on the availability of

1 data) on samples which originally ran CFA, consisted of non-clinical participants, or used
2 English versions of the DASS (see supplementary table 12 for a summary of all such sub-
3 analyses). Of note, much of the item variance was explained by the general factor, implying a
4 strong underlying unidimensional construct.

5 Interestingly, meta-analytic CFAs run only on the DASS42 samples initially found the
6 original 3-factor oblique model of the DASS to fit the data best. However, when DASS21
7 models were re-fitted using data from the same DASS42 samples, the bifactor structure with one
8 general and three group factors was again best fitting. Therefore, the apparent discrepant findings
9 were not due to the characteristics of these DASS42 samples. Instead, the two versions of DASS
10 may indeed have different underlying latent factor structures, which would be congruent with
11 implications from the reviewed studies. Further examinations of this best-fitted DASS42 3-factor
12 model however revealed that the three subscales were perfectly correlated, essentially reflecting
13 a 1-factor model, again indicating strong underlying unidimensionality. It may be that the
14 DASS42 data fit worse to a bifactor model simply due to statistical reasons, as the bifactor model
15 requires more parameters to be estimated. As such, DASS21 data could be more easily fitted to a
16 bifactor structure as its lower item count incurred a lower fitting cost going from a 3-factor
17 model to a bifactor model. In any case, considering the patterns of findings from both our
18 systematic review and meta-analytic factor analyses, it is clear that more research needs to be
19 done concurrently comparing both versions of the DASS, to elucidate whether any differences in
20 their latent factor structure exist.

21 Limitations of our meta-analytic CFA approach also need to be acknowledged here. On
22 one hand, the approach we took in generating implied item correlation matrices allowed us to
23 utilize data from a larger number of samples than would normally be possible, as factor-analytic

studies do not commonly report raw correlation matrices. However, this approach might also bias the findings towards the best-fitted models from the included studies.

Broader implications of the current findings

The key notion of there being a strong element of unidimensionality underlying the DASS adds to the extensive literature demonstrating the overlap between depression and anxiety, as well as ongoing research efforts to reconceptualize our theoretical organization of psychopathology by explicitly taking such empirical higher-order overlaps into account (e.g. Brown, Chorpita, & Barlow, 1998; Clark & Watson, 1991; Eysenck, 1970; Kotov et al., 2017; Watson & Tellegen, 1985; Zinbarg & Barlow, 1996; Waszczuk et al., 2017; Watson, 2009). Of note, depression and anxiety have consistently been subsumed under some form of shared element throughout all the propositions of alternative psychopathological models over the years. These research efforts are starting influence clinical practice, namely in the upcoming Transdiagnostic Approach towards psychopathology (Norton & Paulus, 2017; Norton & Phillip, 2008), which advocates for the treatment of identifiable symptoms without being constrained by their diagnostic labels. This can mean prescribing the same treatment for depression and anxiety to alleviate their shared symptoms, in a bid to better combat issues of comorbidity (Newby et al., 2015). Our findings likewise add to the rationale of adopting such intervention approaches.

Future Directions and Conclusion

Moving forward, some general recommendations are put forth regarding the DASS in light of our current findings. More consideration should be given to the psychometric properties of the DASS using better statistical practices. For EFA, this may include using Principal Axis Factoring over Principal Components Analysis, and utilizing oblique or bifactor rotations rather than orthogonal ones. For CFA, it may be beneficial to fit the models with a Weighted Least

Squares rather than Maximum Likelihood approach, and to avoid arbitrary adjustment of the model based on modification indices. It must also be acknowledged that bifactor modeling techniques, while providing researchers an intuitive method to model psychopathology, are not perfect. As outlined by Bonifay, Lane, and Reise (2017), good psychometric fit of psychopathological constructs to a bifactor structure does not necessarily indicate valid real-life relationships between said constructs, especially considering the tendency of said structure to demonstrate superior goodness of fit due to “overfitting”. In the current case, our findings are corroborated by converging empirical and theoretical evidence, though it is nonetheless important to remain mindful of the explanatory limitations of bifactor models alone.

Theoretically speaking, our work adds to the strong support for the theoretical construct of a general distress factor underlying depression and anxiety. Future research should aim at developing a better understanding of this construct, for instance by investigating its associations with other traits within the wider population. On a practical note, due to the potential applicability of a bifactor structure to the DASS, researchers and practitioners should at least be aware that the score of each subscale is the function of some shared as well as specific elements. As such, straightforward usage of the raw DASS subscale scores separately—as is the current standard usage of the DASS—may not provide the full picture of one’s symptom profile. Given our observed high explanatory power of a general underlying factor, it may also be meaningful to use the DASS total score as a more general measure of distress or psychopathology. All in all, the DASS affords researchers a useful tool via which we can further our understanding of psychopathological dimensionality, and the growing volume of data from its increasingly widespread usage is a resource with much potential to be harnessed.

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5

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Tables

Table 1. Meta exploratory factor analyses: factor loadings from three different rotation/extraction methods (performed on a co-occurrence matrix constructed with the data from 18 samples)

	Crawford-Ferguson Rotation (Oblique)			Jennrich-Bentler Rotation (Orthogonal Bifactor)				Schmid-Leiman Transformation (Orthogonal Bifactor)			
<i>Item No.</i>	<i>F1</i>	<i>F2</i>	<i>F3</i>	<i>General</i>	<i>F1</i>	<i>F2</i>	<i>F3</i>	<i>General</i>	<i>F1</i>	<i>F2</i>	<i>F3</i>
D3	0.02	-0.93	0.07	0.44	-0.85	0.00	-0.04	0.49	0.81	0.01	0.02
D5	0.22	-0.80	0.06	0.54	-0.70	-0.11	0.14	0.53	0.69	0.17	0.01
D10	-0.03	-0.97	0.07	0.42	-0.89	0.03	-0.07	0.49	0.85	-0.04	0.03
D13	0.18	-0.83	0.06	0.53	-0.73	-0.09	0.10	0.53	0.72	0.14	0.02
D16	0.12	-0.94	-0.04	0.43	-0.86	-0.10	0.06	0.50	0.82	0.09	-0.08
D17	-0.03	-0.97	0.02	0.37	-0.89	0.01	-0.04	0.46	0.85	-0.04	-0.02
D21	-0.05	-0.97	0.08	0.42	-0.88	0.05	-0.08	0.48	0.85	-0.05	0.04
A2	0.13	0.07	0.87	0.84	0.23	0.26	-0.13	0.47	-0.08	0.09	0.75
A4	0.01	-0.06	0.87	0.84	0.11	0.35	-0.13	0.47	0.04	0.00	0.76
A7	-0.03	0.06	0.96	0.77	0.22	0.35	-0.34	0.43	-0.07	-0.03	0.84
A9	0.19	0.00	0.73	0.63	0.07	-0.01	-0.59	0.47	-0.02	0.15	0.62
A15	0.11	-0.14	0.76	0.65	-0.06	0.05	-0.66	0.51	0.11	0.08	0.65
A19	-0.03	-0.07	0.83	0.80	0.11	0.40	-0.03	0.43	0.05	-0.03	0.72
A20	-0.02	-0.16	0.87	0.72	-0.03	0.25	-0.52	0.49	0.12	-0.03	0.75
S1	0.77	-0.01	0.01	0.56	0.05	-0.51	0.32	0.44	-0.02	0.63	-0.03
S6	0.94	-0.03	0.01	0.55	-0.02	-0.78	-0.06	0.54	-0.01	0.78	-0.04
S8	0.93	0.00	0.15	0.67	0.03	-0.71	-0.06	0.60	-0.04	0.77	0.08
S11	0.85	-0.09	0.11	0.63	-0.06	-0.65	-0.04	0.57	0.05	0.70	0.05
S12	0.81	-0.17	0.08	0.67	-0.11	-0.58	0.13	0.58	0.12	0.67	0.03
S14	0.91	-0.02	0.1	0.64	0.01	-0.69	0.01	0.57	-0.02	0.75	0.04
S18	0.91	-0.08	-0.05	0.53	-0.08	-0.76	0.03	0.53	0.04	0.75	-0.09
<i>Interfactor Correlations</i>											
F1	1										
F2	-0.23	1									
F3	0.22	-0.19	1								

Note: Factor loadings above a magnitude of 0.40 are presented in bold.

Table 2. Meta confirmatory factor analysis, model fit statistics

	χ^2	DF	RMSEA	SRMR	CFI	TLI	AIC	BIC
<i>Analysis run on: All DASS42 samples (8 samples, total N = 4796)</i>								
1. [DASS42] 3-factor oblique model	3002.2	816	0.0236	0.1624	0.9210	0.9166	1370.2	-3913.9
2. [DASS42] Bifactor model (1 general distress factor, 2 specific factors of Depression and Anxiety)	2940.3	791	0.0238	0.1592	0.9223	0.9155	1358.3	-3763.8
3. [DASS42] Bifactor model (1 general distress factor, 3 specific factors of Depression, Anxiety and Stress)	2911.2	777	0.0239	0.1579	0.9229	0.9145	1357.2	-3674.3
(4.) (Post-Hoc) [DASS42] 1-factor model	3003.8	819	0.0236	0.1625	0.9210	0.9170	1365.8	-3937.6
<i>Analysis run on: All DASS42 samples (8 samples, total N = 4796)</i>								
1. [DASS21] 3-factor oblique model	1794.1	186	0.0425	0.1208	0.9021	0.8894	1422.1	217.7
2. [DASS21] Bifactor model (1 general distress factor, 2 specific factors of Depression and Anxiety)	1699.6	175	0.0426	0.1149	0.9072	0.8886	1349.6	216.4
3. [DASS21] Bifactor model (1 general distress factor, 3 specific factors of Depression, Anxiety and Stress)	1582.6	168	0.0419	0.1070	0.9139	0.8923	1246.6	158.8
<i>Analysis run on: All DASS42 and DASS21 samples (30 samples, total N = 23176)</i>								
1. [DASS21] 3-factor oblique model	7736.3	186	0.0419	0.1041	0.9047	0.8924	7364.3	5866.8
2. [DASS21] Bifactor model (1 general distress factor, 2 specific factors of Depression and Anxiety)	7229.7	175	0.0417	0.0978	0.9110	0.8932	6879.7	5470.8
3. [DASS21] Bifactor model (1 general distress factor, 3 specific factors of Depression, Anxiety and Stress)	6906.6	168	0.0416	0.0934	0.9150	0.8937	6570.6	5218.1

Note. DF = degrees of freedom; RMSEA = root mean squared error of approximation; SRMR = root mean squared residual; CFI = comparative fit index; TLI = Tucker-Lewis index; AIC = Akaike information criterion; BIC = Bayesian information criterion. Values in bold indicate the best-fitting models in each category.

Table 3. Meta confirmatory factor analysis: factor loadings from the best-fitting DASS21 bifactor model (performed on data from 30 samples, total $N = 23176$)

	General	Depression	Anxiety	Stress	<i>I-ECV</i>
<i>Item No.</i>					
D3	0.77	-0.14	-	-	0.97
D5	0.80	-0.11	-	-	0.98
D10	0.68	-0.04	-	-	1.00
D13	0.69	0.00	-	-	1.00
D16	0.67	0.16	-	-	0.95
D17	0.74	0.11	-	-	0.98
D21	0.72	0.17	-	-	0.95
A2	0.68	-	0.05	-	0.99
A4	0.81	-	0.00	-	1.00
A7	0.79	-	-0.07	-	0.99
A9	0.65	-	-0.01	-	1.00
A15	0.62	-	0.28	-	0.83
A19	0.76	-	0.21	-	0.93
A20	0.69	-	0.04	-	1.00
S1	0.72	-	-	-0.06	0.99
S6	0.80	-	-	-0.01	1.00
S8	0.52	-	-	0.01	1.00
S11	0.69	-	-	0.19	0.93
S12	0.80	-	-	0.23	0.93
S14	0.76	-	-	0.18	0.94
S18	0.78	-	-	0.00	1.00

Note: I-ECV = Item-level expected common variance (i.e. the proportion of variance explained by the general factor out of the total variance explained, for each item).