Original Article

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Confirmatory Factor Analysis of Depression, Anxiety and Stress 21 (DASS 21) scale in a study on Occupational Health Psychology in Health Care Professionals from Anand, Gujarat

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Abstract:

Introduction: Confirmatory factor analysis (CFA) is a statistical technique to verify the factor structure of a set of observed variables. **Objective:** The study was conducted with an objective to study the psychometric properties of DASS 21 scale by Confirmatory factor analysis**. Method:** This study used a Multi Method Design (Multiple approach Design), one was a cross sectional study of 228 participants and the other was a Solomon 4 group Design with total 64 participants. Four groups of health care professionals viz Allopathic doctors, Physiotherapists, Nursing professionals and Community Health Officers (CHOs) were chosen for the study. Convenience sampling was done at two stages. **Results:** Confirmatory factor analysis was used to evaluate the construct validity of DASS 21 scale. The model was overidentified as the estimated parameters were less than the number of observed variances and covariances. CMIN/DF (Chi square (minimum discrepancy function) /Degree of freedom) value was 2.021 which was < 5. Goodness of Fit Index (GFI) value (0.892) was near to .9. Root Mean square Residuals (RMR) and Root Mean Square Error of Approximation (RMSEA) value were 0.031 and 0.063, respectively which were less than 0.08. Average variance extracted (AVE) for the three constructs were less than the squared interconstruct correlation. **Conclusion:** DASS-21 scale demonstrated a good convergent validity, but in this study, discriminant validity was found to be poor as determined by average variance extracted in comparison to squared Interconstruct correlation.

Keywords: Confirmatory factor analysis, DASS 21, Health care professionals, Occupational Health Psychology

Introduction:

Factor analysis is to identify and/or understand the nature of the latent constructs underlying the variables of interest.[1] Confirmatory factor analysis (CFA) is a statistical technique to verify the factor structure of a set of observed variables. CFA tests a hypothesized relationship between observed variables and their underlying latent constructs.[2] Confirmatory factor analysis (CFA) is the fundamental first step before Structural equation modelling (SEM models). These methods explore the relationship between an outcome variable and predictor variables. Factor loadings of the indicators (observed variables) are calculated. Convergent validity is indicated by high factor loadings. Goodness of fit statistics test for absolute, parsimonious, and

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incremental goodness of fit. Confirmatory factor analysis for all constructs is an important first step before developing a structural equation model.[3] Confirmatory factor analysis (CFA) is a powerful statistical tool for examining the nature of and relations among latent constructs.[4] DASS 21 is a Likert scale and is frequently used in research. The scale consists of 7 questions on stress, anxiety and depression and in total 21 questions are there.[5]

Objective:

The study was conducted with an objective to study the psychometric properties of DASS 21 scale by doing Confirmatory factor analysis.

Method:

The current study was done using Multimethod study design in Anand District amongst the healthcare professionals over the study period starting from December 2020 to September 2023. The data collection period was of 2 years (February 2021- Jan 2023).Two study designs were used in this Multi Method study Design (Multiple approach Design). These were 1.Cross sectional study Design: Base pool of participants and 2. Quasi experimental - Solomon four Nonequivalent control group study design for intervention.

Sample size:

For Cross sectional study sample size was calculated using OpenEpi Version 2.3.1 and by the formula= $[DEFF*Np\ (1-p)]/\ [(d2/Z^2_{1-\alpha/2}*(N-1)\ +p*(1-p)]$[6]

In the formula, N- Population size.

Hypothesized % frequency of outcome factor in the population (p)- 50% to keep the maximum sample size for the given set of particulars in sample size calculation.

Absolute Precision %- 7%

Confidence limits as % of 100-/+ 7%

$Z^2_{1-\alpha/2}$= Standard normal variate (at 5% type I error p= 0.05, it is 1.96)

DEFF- Design effect-1

Confidence level - 95%

Based on the “p” and at 95% confidence limit, the calculated sample size was 196. Considering 10 % non-response rate, the final sample size came to 216. The data collection was done for 231 participants and during data entry, 3 proformas with incomplete information for the 9 scales were rejected. So, the final base pool of participants was 228.

Sample size for Solomon 4 group Design was calculated by using GPower 3.1[7] for F tests: ANOVA: Repeated measures, within-between interaction

Effect size f = 0.25

α error (prob) = 0.05

Power = 0.90

Number of groups = 4

Keeping the intervention group participants in the overall sample size, the sample increased by 32 participants over the base sample from Group III and Group IV of Solomon 4 Group Design.

Cross sectional study of 228 participants in phase I was done followed by Solomon 4 group Design with a total 64 participants. Total 32 participants were from original frame as Group I and Group II participants. So, 32 participants additional to 228, 260 was the overall sample size.

This study was approved by the Institutional Ethics committee and the clearance number was IEC/ HMPCMCE/ 122/ Faculty/ 4/. All the participants have filled the informed consent form. The data was analyzed by SPSS version 15.0 (SPSS Inc., Chicago, IL, USA) and trial version AMOS 26.0 graphical interface (SPSS Inc.).

Inclusion criteria: Those who agreed to participate in the study and with minimum of 1 year of exposure to work in the same profession and at the same place, working only in an institution either Government or private.

Exclusion criteria: There was as such no exclusion criteria.

Different health care professionals viz Allopathic doctors, Physiotherapists, Nursing Professionals and Community Health Officers (CHOs) were included as study participants.

Sampling was convenient sampling and done in 2 stages

Stage 1: Primary units (Institutions and Government Public health facilities)

Participants were selected from:

1. One Medical college and hospital
2. One Nursing school
3. Two District blocks
4. Civil hospital
5. Three Physiotherapy colleges

Stage 2: Participants from the institutions: Those who agreed to participate and were in the inclusion criteria.

1. Medical college hospital: Doctors were selected
2. Nursing school: Nursing professionals were selected
3. District blocks: Nursing professionals and CHOs were selected
4. Civil hospital: Doctors were selected
5. Physiotherapy colleges: Physiotherapists were selected

Different organizations were taken as the entire pool was not available at a single institute and varied responses related to govt and private organizations was to be seen in relation to employer care and other such occupational attributes. In this study, 49 Allopathic Doctors, 112 Physiotherapists, 51 Nursing professionals and 48 Community health officers (CHO) participated.

Selection of questionnaires: To meet the desired objectives of the overall project, 9 scales/ questionnaires along with a socio-demographic proforma including occupational attributes and a proforma for qualitative study in form of "Open ended questions" was finalized. Out of these 9 scales, one was DASS 21. The current manuscript is about the Confirmatory factor analysis to study the psychometric properties of DASS 21 scale. All the 21 variables were coded as DASS1 to DASS21.

Respondents rate items on a 4-point Likert scale, ranging from 0 - "Didn't apply to me at all- Never" to 3 - "Applied to me very much, or most of the time."

Final outcomes were coded as S , D and A. The final score for a particular construct is by multiplying with 2. The specific questions for a particular construct were

S (Stress)= (DASS1+ DASS6+ DASS8+ DASS11+ DASS12+ DASS14+ DASS18) *2

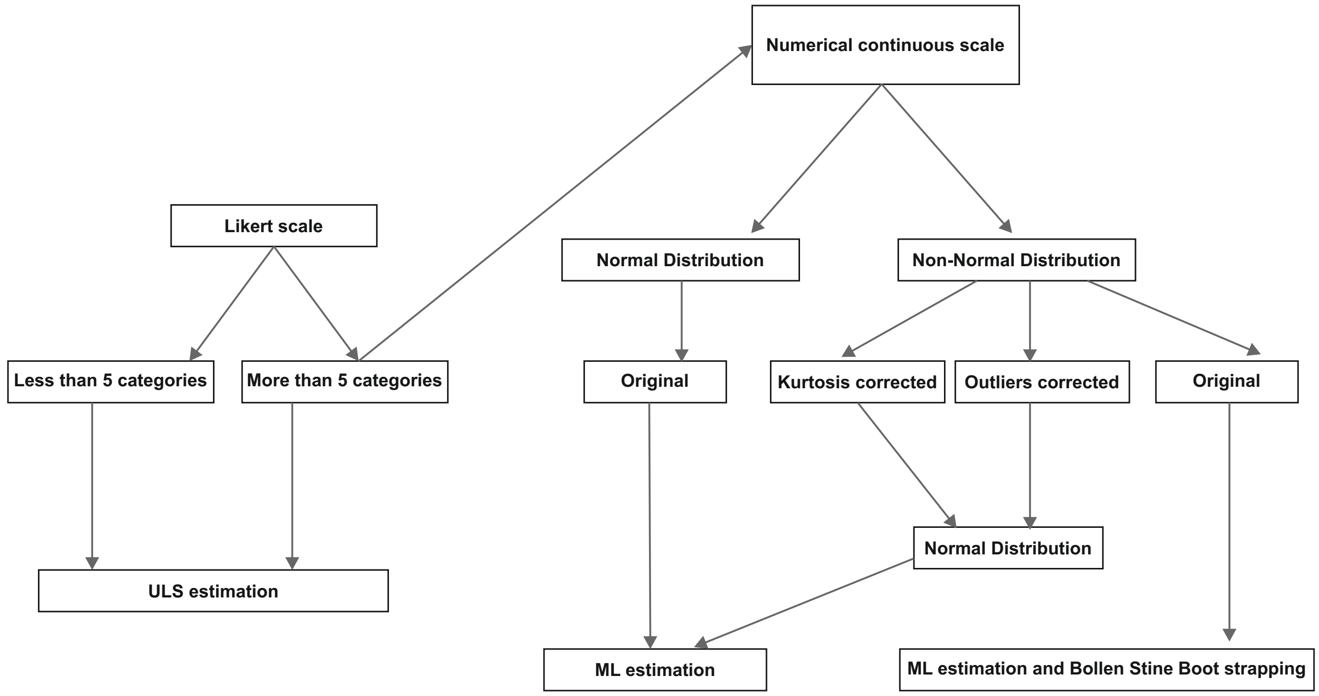
A (Anxiety)= (DASS2+ DASS4+ DASS7+ DASS9+ DASS15+ DASS19+ DASS20) *2

D (Depression)= (DASS3+ DASS5+ DASS10+ DASS13+ DASS16+ DASS17+ DASS21) *2

Results:

This study was an attempt to assess the relative performance of continuous and categorical estimation methods in the same sample, with the underlying assessment of univariate and multivariate normality assumptions. All the 4 identified Data sets were of the same data and these were identified based on the theoretical consideration for continuous data and the Likert scale. In theoretical consideration for continuous data, 1) First Data set was naïve data, 2) Second Data set was with the correction for normality based on Kurtosis >2, 3) Third Data set was with complete correction for outliers and 4) Fourth Data set was considering the naïve data as on Likert scale. ML (Maximum Likelihood) method of estimation was usedin the first 3 Data sets considering the data set as on continuous numerical scale and was applied Bollen Stine bootstrapping correction for the non-normality. For the Likert scale, was used. ULS (Unweighted Least Square) estimation method. The metrics of model fit indices mentioned are of Data set 1.

Figure 1: Outline showing the 4 studied Data sets for CFA analysis



Normality Assessment:

Mardia's statistic for multivariate normality was used.[8] Multivariate outliers were identified by Mahalanobis distance (Squared).[9] Bollen-Stine bootstrap procedure was applied in the non-normal data as seen here and it helps in accommodating the negative distributional properties of the data.[10]

Calculation of Construct reliability (a measure of convergent validity with AVE) and Divergent validity.

CFA measures construct validity. It comprises of convergent and divergent validity. Item reliability is square of the factor loadings which are standardized estimates. Delta is calculated as 1- Item reliability. AVE is total summation of squared factor loadings or summation of item reliability of a construct divided by the total variables in that construct. Construct reliability is square of the summation of factor loadings divided by the total sum of square of the summation of factor loadings and total delta sum of that construct.

Item reliability IR = $(FL)^2$

Delta= 1-IR

AVE= Sum of $(FL)^2$/Total number of variables of the same construct

CR= $(\text{Sum FL})^2/[(\text{Sum FL})^2 + \text{Sum (Delta)}]$

DASS-21 scale along with standardized regression weights (factor loadings). Significance of the particular item /variable is also shown.

Table 1 shows the maximum likelihood estimates for the different items/variables of DASS-21 scale along with standardized regression weights (factor loadings). Significance of the particular item /variable is also shown.

In this scale, all the measured variables kurtosis was less than 2, except DASS 4 and 7. Mardia's coefficient 180.69 was lower than 440 i.e p (p+2) where p was 20 here. Mahalanobis Distance (Squared) was 83.90 and it was more than the chi-square value (for the degree of freedom equals to the number of variables) at p<.001 (45.31), so it is suggestive of outliers. Mahalanobis distance (squared) has also reduced to a great extent from Data set 1 to Data set 3. (Table 2)

Table1: Maximum Likelihood Estimates and Standardized Regression Weights for DASS 21

Variables		Constructs	Estimate	S.E.	C.R.	P	Standardized Regression Weights
DASS1	<—-	Stress	1.000				.531
DASS6	<—-	Stress	.945	.134	7.079	<.001	.564
DASS8	<—-	Stress	1.251	.169	7.418	<.001	.688
DASS11	<—-	Stress	1.342	.170	7.898	<.001	.757
DASS12	<—-	Stress	1.474	.154	9.542	<.001	.776
DASS14	<—-	Stress	1.411	.163	8.675	<.001	.803
DASS18	<—-	Stress	1.214	.173	7.014	<.001	.619
DASS20	<—-	Anxiety	1.000				.710
DASS19	<—-	Anxiety	.977	.101	9.658	<.001	.629
DASS15	<—-	Anxiety	1.220	.097	12.626	<.001	.828
DASS9	<—-	Anxiety	1.160	.113	10.279	<.001	.720
DASS7	<—-	Anxiety	.825	.087	9.484	<.001	.618
DASS4	<—-	Anxiety	.551	.071	7.788	<.001	.506
DASS3	<—-	Depression	1.000				.582
DASS5	<—-	Depression	.838	.109	7.668	<.001	.567
DASS10	<—-	Depression	1.114	.118	9.426	<.001	.756
DASS13	<—-	Depression	1.246	.131	9.488	<.001	.766
DASS16	<—-	Depression	1.288	.132	9.781	<.001	.804
DASS17	<—-	Depression	1.166	.125	9.357	<.001	.751
DASS21	<—-	Depression	1.118	.128	8.711	<.001	.673

SE- Standard error, CR- Critical ratio, P- p value

All the metrics of model fit indices were judged against the specific values as suggested by authors given in the last column. (Table 3)

Data set 1 is taken as reference for the model figure and the calculations in Table 4.

All the construct's AVE estimates were lesser than the corresponding squared Interconstruct correlation estimates suggesting poor divergent validity. (Table 4)

Discussion:

In this study, all the factor loadings (Standardized regression weights) for DASS 21items/ variables were above 0.5 except DASS 2 (.322) in anxiety domain. All the items/variables having significant p

Table 2 : Univariate and multivariate normality of the assessed variables of DASS 21

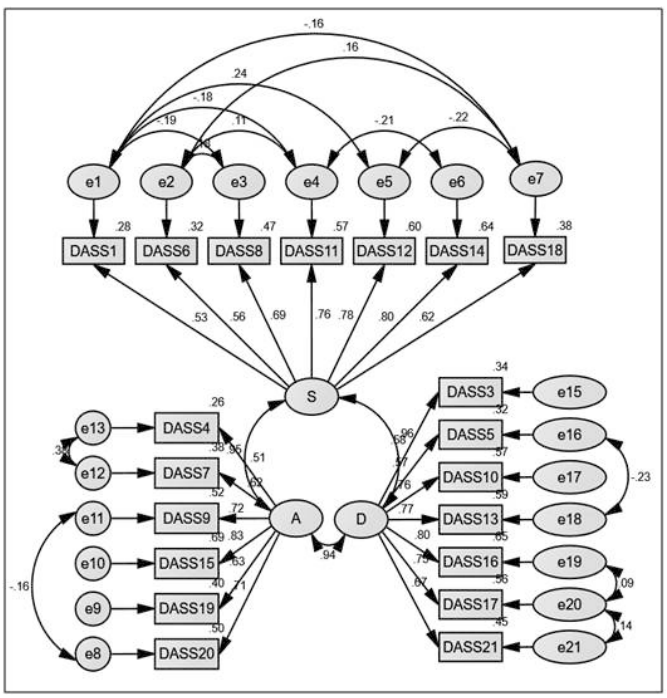
Variables	Data Set 1 (Original)				Data Set 2 (>2 Kurtosis Corrected)				Data Set 3 (Outliers corrected)			
	Skewness	Critical ratio(CR)	Kurtosis	CR	Skewness	CR	Kurtosis	CR	Skewness	CR	Kurtosis	CR
DASS21	1.40	9.22	0.99	3.26	1.40	9.22	0.99	3.26	0.98	6.42	-0.52	-1.70
DASS17	1.22	8.04	0.77	2.53	1.22	8.05	0.77	2.53	0.81	5.31	-0.69	-2.28
DASS16	1.08	7.15	0.42	1.39	1.09	7.15	0.42	1.39	0.65	4.30	-0.92	-3.02
DASS13	0.92	6.08	0.09	0.30	0.92	6.08	0.09	0.30	0.49	3.21	-1.09	-3.60
DASS10	1.22	8.06	0.88	2.89	1.23	8.07	0.88	2.89	0.85	5.57	-0.57	-1.88
DASS5	0.89	5.89	0.46	1.53	0.90	5.89	0.46	1.53	0.42	2.73	-0.91	-2.98
DASS3	0.89	5.89	-0.25	-0.83	0.90	5.90	-0.25	-0.83	0.54	3.55	-1.24	-4.06
DASS4	2.17	14.28	5.05	16.60	1.67	11.00	1.83	6.02	1.68	11.00	1.83	6.02
DASS7	1.66	10.93	2.48	8.18	1.13	7.44	0.11	0.36	1.13	7.44	0.11	0.36
DASS9	1.05	6.93	0.27	0.88	1.05	6.94	0.27	0.88	0.57	3.77	-1.03	-3.40
DASS15	1.05	6.96	0.50	1.63	1.06	6.96	0.50	1.63	0.62	4.10	-0.88	-2.90
DASS19	0.83	5.52	-0.11	-0.37	0.84	5.52	-0.11	-0.37	0.44	2.90	-1.17	-3.85
DASS20	1.12	7.40	0.54	1.78	1.13	7.40	0.54	1.78	0.80	5.26	-0.68	-2.24
DASS18	0.62	4.14	-0.61	-2.00	0.63	4.14	-0.61	-2.00	0.60	3.96	-0.65	-2.13
DASS14	0.86	5.67	0.14	0.45	0.86	5.67	0.14	0.45	0.46	3.01	-1.02	-3.36
DASS12	0.75	4.95	-0.25	-0.81	0.75	4.95	-0.25	-0.81	0.33	2.15	-1.24	-4.08
DASS11	0.98	6.49	0.53	1.74	0.99	6.50	0.53	1.74	0.46	3.04	-0.93	-3.06
DASS8	0.80	5.28	-0.05	-0.16	0.80	5.28	-0.05	-0.16	0.39	2.55	-1.13	-3.71
DASS6	0.47	3.12	-0.43	-1.43	0.48	3.13	-0.43	-1.43	0.20	1.32	-1.11	-3.66
DASS1	0.77	5.12	-0.10	-0.31	0.78	5.13	-0.10	-0.31	0.30	1.98	-1.17	-3.85
Mardias coefficient			180.69	49.10			173.64	47.19			108.72	29.55
Variables	20 x 22= 440				20 x 22= 440				20 x 22= 440			
Mahalan-obis distance-(Squared)	83.9				84.18				57.46			
Chi Square p<.001	45.31				45.31				45.31			

Table 3 : Metrics of Model Fit Indices for 4 Data Sets based on the normality assessment and estimation method

	IndicesValues in this model DASS-21				**Suggested value**
	Data Set 1 (Original)	**Data Set 2 (>2 Kurtosis Corrected)**	**Data Set 3 (Outliers corrected)**	**Data Set 4 (Original)**	
	ML estimation			**ULS**	
CMIN/DF	2.021	2.045	1.885	CMIN 49.954	< 5.00 (Hair JF et al.)[11]
GFI	0.892	0.888	0.902	0.992	> 0.90 (Hu LT and Bentler PM) [12]
AGFI	0.852	0.849	0.865	0.989	> 0.90 (Hair JF et al.)
CFI	0.944	0.942	0.948		> 0.90 (Hooper D et al.)[13]
NFI	0.897	0.894	0.897	0.99	> 0.90 (Hu LT and Bentler PM)
TLI	0.931	0.929	0.936		> 0.90 (Hooper D et al.)
RMR	0.031	0.031	0.023	0.03	< 0.08 (Hair JF et al)
RMSEA	0.063	0.064	0.058		< 0.08 (Hair JF et al.)
Parsimony Adjusted Measures					
PNFI	0.722	0.729	0.723	0.797	>.5(Hooper D et al.)
PCFI	0.76	0.768	0.764		>.5(Hooper D et al)
Cronbachs Alpha	S=.85 A=.83 D=.87	S=.85 A=.83 D=.87	S=.84 A=.83 D=.86		>.7
Bollen-Stine Bootstrap	0.05				

CMIN/DF- Chi square /Degree of freedom, GFI- Goodness of Fit Index , AGFI- Adjusted Goodness of Fit index, NFI- Normed Fit Index, CFI- Comparative Fit Index , TLI- Tucker Lewis index, RMR- Root Mean square Residuals, RMSEA- Root Mean Square Error of Approximation, PNFI- Parsimony normed fit index, PGFI- Parsimony goodness of fit index

Figure 2: CFA model DASS 21



Stress, A- Anxiety and

D- Depression Latent Constructs

DASS 1/2/...... Observed variables

e-error term

Double arrow- Co-variances

Table 4 : Calculation and Comparison of Construct reliability (CR), AVE and Squared Interconstruct correlation with inference for Convergent and Discriminant validity for DASS 21

Factors	Direction	Constructs	Estimate (Standardized) FL	IR	Delta	Sum IR	AVE	Sum Delta	Sum FL	Square Sum FL	CR	Squared Interconstruct correlation
DASS1	<—-	Stress	0.53	0.28	0.72							Stress X
DASS6	<—-	Stress	0.56	0.32	0.68							Anxiety
DASS8	<—-	Stress	0.69	0.47	0.53							0.9
DASS11	<—-	Stress	0.76	0.57	0.43							
DASS12	<—-	Stress	0.78	0.60	0.40							Stress X
DASS14	<—-	Stress	0.80	0.64	0.36							Depression
DASS18	<—-	Stress	0.62	0.38	0.62	3.28	0.47	3.72	4.74	22.45	0.86	0.92
DASS20	<—-	Anxiety	0.71	0.50	0.50							Anxiety X
DASS19	<—-	Anxiety	0.63	0.40	0.60							Depression
DASS15	<—-	Anxiety	0.83	0.69	0.31							0.87
DASS9	<—-	Anxiety	0.72	0.52	0.48							Anxiety X
DASS7	<—-	Anxiety	0.62	0.38	0.62							Stress
DASS4	<—-	Anxiety	0.51	0.26	0.74	2.74	0.46	3.26	4.01	16.09	0.83	0.90
DASS3	<—-	Depression	0.58	0.34	0.66							Depression X
DASS5	<—-	Depression	0.57	0.32	0.68							Anxiety
DASS10	<—-	Depression	0.76	0.57	0.43							0.87
DASS13	<—-	Depression	0.77	0.59	0.41							
DASS16	<—-	Depression	0.80	0.65	0.35							Depression X
DASS17	<—-	Depression	0.75	0.56	0.44							Stress
DASS21	<—-	Depression	0.67	0.45	0.55	3.48	0.50	3.52	4.90	24.00	0.87	0.92

Legends: IR: Item reliability, AVE-Average variance extracted, FL: Factor loading (Standardized estimates), CR- Construct reliability values and standardized regression weights as more than .5 were kept for further analysis, so DASS 2 item was removed and not taken forward. (Table 1). Univariate and multivariate normality are basic assumptions in CFA using ML method of estimation. In this study, both the univariate and multivariate normality were assessed. (Table 2). In order to prove normal univariate distribution, as per George and Mallery, the values for asymmetry and kurtosis between -2 and +2 are considered as acceptable.[14] Different such cut off values were suggested by other authors. Kurtosis values greater than 3 in magnitude may indicate the non-normal distribution of the variable as mentioned by Westfall and Henning.[15] Cut-off values of 3 for univariate skewness and 7 for univariate kurtosis have been proposed by West et al[16] Gravetter and Wallnau suggested acceptable limits as ±2.[17] Curran et al. suggested these same moderate normality thresholds of 2 and 7 for skewness and kurtosis respectively when assessing multivariate normality.[18] Mardia's coefficient if lower than p(p+2), where p is the number of variables studied, then the combined distribution of the variables is multivariate normal.[8] There are many recommendations related to the limits of kurtosis and skewness for normality and themselves are not uniform. Skewness index and Kurtosis index are important measures of normality. (Table 2) Ding et al. recommended a minimum sample size of 100 and 3 indicators per factor in order to use ML estimation appropriately.[19] We had a sufficient sample of 260. We found a very narrow difference in all the 4 data sets and all suggesteda good model fit based on the metrics of model fit indices, with the increasing value of fit indices as we move from 1st Data set to 3rd Data set. (Figure 1) In a study at University of Pretoria, Mardia's statistic showed multivariate normality in presence of univariate non-normality and that happened to be a limiting factor for ML estimation procedures.[20] When the data is a Likert scale, the other estimation methods are suggested. In this study, we have analyzed how the metrics of model fit indices changes on framing 4 Data sets with specific distribution and estimation method. Browne used ULS (Unweighted least squares) and RULS (Robust ULS)to account for ordinal data.[21] Two suggested methods are unweighted least square (ULS) and diagonally weighted least square (DWLS). We found slight difference between the indices by ML and ULS estimation. In ULS estimation, different indices value haveincreased as compared to ML estimation and RMR has slightly decreased. (Table 3) Psychometric properties of Depression, Anxiety and Stress 21 scale (DASS 21): Total number of variables in the model were 43, 23 exogenous and 20 endogenous. Number of possible variances and covariances among the items/variables = (20x21)/2=210. p(p+1)/2 where p is endogenous variables. p is 20, no of endogenous variables. Total number of parameters observed were 80, this in particular is AMOS output. (20x21)/2=210 is > 80, so this model is overidentified. A model should be overidentified.[22] The number of parameters that are being estimated needs to be less than the number of variances and covariances observed and this is called an overidentified model. So, this model was overidentified. All the measured variables kurtosis were less than 2, except DASS 4 and 7. DASS 2 was deleted as the standardized regression weight was less than .5. Mardia's coefficient (180.69) was less than 440 20(22) in all the 4 data sets, proving multivariate normality. Mahalanobis Distance (Squared) was 83.90 and it was more than the chi-square value (for the degree of freedom equals to the number of variables) at p<.001 (45.31), so it was suggestive of outliers. Multivariate normality measure and Mahalanobis distance-(Squared) has reduced from Data set 1 to 3. Owing to univariate nonnormality in DASS 4 and 7, Bollen Stine Bootstrapping procedure was applied and it was .05, suggesting good model fit. This should be non-significant for model to be fit. The Bollen-Stine bootstrap procedure was used to counter the negative distributional properties of the data because of multivariate nonnormality.[10] The metrics of model fit indices were assessed. CMIN/DF value was 2.021 which was< 5. Goodness of Fit Index (GFI) value (0.892) was near to .9. The Normed Fit Index (NFI) value (0.897), Comparative Fit Index (CFI) value (0.944) and Tucker Lewis index (TLI) value was (0.931) were above 9 as suggested. Root Mean square Residuals (RMR) and Root Mean Square Error of Approximation (RMSEA) value were 0.031 and 0.063 respectively which were less than 0.08. Parsimony adjusted measures were more than 0.5. Morrison et al have given a vivid description of all these indices.[22] (Table 3). The model fit indices have increased as we move from Data set 1 to set 4. The results showed that ULS lead to smaller RMR and larger CFI and TLI values than does ML estimation. Construct reliability along with AVE is a measure of convergent validity. Ideally AVE should be more than .5, but when the construct reliability is more than .7, its lesser value is not a problem. Construct's AVE estimates (from .46 to .50) were lesser than the corresponding squared Interconstruct correlation estimates suggesting poor divergent validity between stress, depression and anxiety. Covariances and modifications were shown in Figure 2. In our study, we got Cronbach's alpha as stress .85, anxiety .83 and depression as .87.Cao et al. in their study mentioned that DASS-21 scale demonstrated a high degree of internal consistency (Cronbach's alpha >0.85), and good convergent validity. Discriminant validity was poor as determined by average variance extracted.[23] (Table 4). DASS-21 had difficulty in properly identifying and discriminating between symptoms associated with depression and anxiety in study in Hispanic population.[24] The study by Lee has provided evidence regarding the convergent, discriminant, and nomological validity of DASS-21 through CFA.[25]

Conclusion:

DASS-21 scale demonstrated a good convergent validity, but discriminant validity was poor as determined by average variance extracted in comparison to squared interconstruct correlation in this study.

Declaration:

This manuscript is one of the manuscripts from a PhD study on Occupational health Psychology done in health care professionals. The details in materials and methodology remain same in the papers/ manuscripts with specific emphasis for particular objective in the paper/manuscript. Each of the manuscripts caters to a particular domain and is related to specific objective. The detailed scoring of DASS 21 constructs and associations with other variables are published in a separate paper and the interested readers can read from the paper1 and the translation details and other detailing of participants involvement can be read from paper 2

Paper1: Sharma DB, Sharma HK. An epidemiological study on occupational health psychology in health care professionals (doctors, physiotherapists, nursing professionals and community health officers). Int J Health Sci Res. 2023; 13(3):174-186.

Paper 2: Sharma DB, Sharma HK. The Translation Process, Validity and Reliability Study in Occupational Health Psychology amongst Healthcare Professionals by Multitrait-Multimethod Matrix: A Multimethod Study. Clin of Diagn Res.2023; 17(6):VC08-VC13.)

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