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THE DIMENSIONALITY OF THE GENERAL WORK STRESS SCALE: A HIERARCHICAL EXPLORATORY FACTOR ANALYSIS

GIDEON P. DE BRUIN
gpdb@rau.ac.za
Department of Human Resource Management
University of Johannesburg

ABSTRACT

This study examined the dimensionality or factor structure of the General Work Stress Scale (GWSS), which is a brief measure of subjectively experienced or felt work stress. The responses of two independent groups of adult workers were subjected to maximum likelihood factor analysis. In both groups a three factor solution provided the best fit with the data. A higher order factor analysis with an orthogonal Schmid-Leiman transformation showed that in both groups, responses to the items are dominated by a general factor, which might be labelled General Work Stress. Three minor group factors were identified: a motivational factor reflected by a desire to leave the organisation, an affective factor reflected by a tendency to worry, and a cognitive factor reflected by concentration and attentional difficulties. Overall, the results provide support for the construct validity of the GWSS as a measure of subjectively experienced work stress.

Key words
Genral work stress, factor analysis

The General Work Stress Scale (GWSS) is a brief self-report measure of an individual's overall level of subjectively experienced or "felt" work related stress. It aims to provide an answer to the following question: How stressed is this person at work? The scale forms part of the Sources of Work Stress Inventory (De Bruin & Taylor, 2006a), which also includes scales of different sources of work stress, namely role ambiguity, poor working relationships, inadequate tools and equipment, job insecurity, limited career advancement prospects, difficulty in balancing work and home demands, lack of autonomy, and excessive workload.

It appears relevant to study subjectively experienced work stress because it has potentially negative effects on the health, psychological well-being, and social functioning of individuals and the functioning of organisations (Cooper, Dewe & O'Driscoll, 2001). From an individual perspective, stress is related to a wide variety of health related problems, including anxiety, headaches, depression, influenza, coronary disease, and substance abuse (Van der Doef & Maes, 1999; Leitner & Resch, 2005; Wiesner, Windle & Freeman, 2005). Stress also has a negative impact on people's cognitive functioning and may contribute to impaired memory, concentration and attention (Smith, 1990; van der Linden, Keijsers, Eling & van Schaijk, 1995). In addition, stress is often accompanied by unpleasant emotions such as anxiety, low mood, anger, and low job satisfaction (Coetzee & Rothmann, 2005; Kahn & Boysiere, 1992). In turn these emotions may lead to aggressive and disruptive behaviour, social withdrawal, disengagement and low job commitment. From an organisational perspective, stress can lead to low productivity, absenteeism, employee burnout, staff turnover, and increased compensation claims (Grobler, Wärnich, Carrell, Elbert & Hatfield, 2002; Jackson & Rothmann, 2006; Tubre & Collins, 2000).

Two perspectives of stress appear to dominate the stress literature, namely an environmental perspective and a transactional perspective. The environmental perspective holds that certain events and situational factors are inherently stressful and that exposure to these events or situational factors result in dysfunction. For instance, Karasek's (1979) Job Demands-Control model of job strain postulates that two situational factors, namely job demands and job control interact to produce working environments that lead to different levels of job strain. Specifically, environments that pose high demands and offer low control in regard to how individuals choose to perform their jobs lead to the highest levels of job strain, whereas environments with low demands and high control lead to the lowest levels of job strain. A large body of research have shown that excessive job demands and low job control are related to negative physical and psychological health outcomes (Van der Doef & Maes, 1999). Many different measures of situational factors have been developed, which include the Job Stress Survey (Spielberger & Reheiser, 1995), the Job Stress Index (Sandman, 1992), and recently the Job Demands-Resources Questionnaire (Jackson & Rothmann, 2005). Generally, these measures focus on the assessment of the severity and frequency of stressors in the working environment and individuals with high scores are assumed to experience greater amounts of stress.

In contrast to the environmental perspective, which emphasises normative antecedents of stress, the transactional perspective emphasises stress as a process where an individual cognitively appraises his or her resources to meet the external or internal demands of a situation (Lazarus & Folkman, 1984). Stress results when the outcomes of the appraisal indicate that the demands exceed the individual's resources. The transactional perspective recognises that certain situations are more stressful than others, but it emphasises that different individuals may appraise the same situation differently. Hence, in contrast to the environmental perspective the transactional perspective views sources of stress as an individual matter (Lazarus, 1995). In addition, the transactional perspective emphasises stress as a dynamic process that recognises that people and environments change. This implies that people's appraisals of situations will vary over time.

The GWSS serves as a measure of the degree to which people appraise their working environments as stressful. In this sense the GWSS is similar to the Perceived Stress Scale (Cohen, Karmack & Mermelstein, 1983), which measures the degree to which people appraise situations in their lives as stressful. In accordance with Hendrix, Summers, Leap and Steel (1995), the focus of the GWSS is on "felt" stress. Put differently, work stress is viewed as an uncomfortable state of psychological tension that results from an appraisal that the perceived demands of the workplace exceeds the individual's perceived resources to successfully meet the demands. This view allows for the possibility that different people may view the same working situation as differentially stressful (Summers, DeCotiis & DeNisi, 1995). Felt stress or perceived stress may be viewed as an intervening variable located between stressful events or situational factors and strain outcomes, such as illness, depression, and job dissatisfaction (Hendrix et al., 1995).

The GWSS consists of nine items that tap into emotional, cognitive, motivational and social consequences of the interaction between an individual and the perceived demands of the workplace. The GWSS is intended to function as a brief unidimensional indicator of work stress, which implies that a single total score is used as a summary statement of an individual's overall level of subjectively experienced work stress or job strain. Persons who obtain high scores are assumed to experience high levels of work stress, whereas individuals who obtain low scores are assumed to experience low levels of work stress.

It is necessary to empirically examine the dimensionality of the GWSS, because the dimensionality of a scale is closely tied to its construct validity (McDonald, 1999). For instance, it may happen that the empirical dimensionality of the GWSS diverges from the theoretical unidimensional structure, which would imply that inferences made from the total score in regard to a person's general work stress may be invalid. Unidimensionality, however, is a matter of degree rather than an absolute condition (Andrich, 1988) and evidence of multidimensionality in the responses to a set of items can always be found, depending on how closely one wishes to look. The assumption of unidimensionality implies that a single construct or dimension underlies the nine items and that this single dimension dominates other minor dimensions that may also be measured by the items (McDonald, 1999). Hence, what is needed is an empirical demonstration that a single common dimension sufficiently accounts for the responses to the items of the GWSS so that the calculation of a total score can be justified.

Against this background the aim of the present study is to examine the dimensionality or factor structure of the GWSS in respect of two independent groups of participants. It is expected that a single dimension or general factor will dominate the responses to the items. However, an exploratory analysis is performed, which explicitly allows for the identification of dimensions or factors other than the general factor if such dimensions are present in the data.

RESEARCH DESIGN

Participants

The participants in Group 1 were 475 employees at two higher education institutions (202 men and 273 women). The mean age was 37.44 years (SD = 11.66 years). The participants in Group 2 were 477 employees at a large South Africa chemical company (97 women, 292 men and 88 of unknown gender). The mean age was 41.32 years (SD = 9.00 years). The participants in Group 1 volunteered to participate in a stress survey done at the two institutions. The participants in Group 2 completed the GWSS as part of a staff development programme.

Measuring Instrument

The participants responded to the items of the GWSS on a five-point Likert scale, where the response options were labelled as 1 = Never, 2 = Rarely, 3 = Sometimes, 4 = Often, and 5 = Always. A sample item is "Does work make you so stressed that you find it hard to concentrate on your tasks?" The reliability of the obtained scores, as estimated by Cronbach's alpha coefficient, for Group 1 and Group 2 were 0.89 and 0.88, respectively. De Bruin and Taylor (2006a) showed that scores on the GWSS are strongly related to a variety of job stressors (including excessive workload, role ambiguity and poor interpersonal relations). De Bruin and Taylor (2006b) reported that the items of the GWSS fit the requirements of the Rasch rating scale model, which is one of a family of item response theory models. De Bruin and Taylor (2006b) also conducted a joint factor analysis of the job demands, job control and GWSS items, and found that the items constituted three separate scales. Jointly, these results provide support for the construct validity of the GWSS.

Analysis

In this study maximum likelihood factor analysis, which is one form of common factor analysis, is used to examine the dimensionality of the GWSS. Common factor analysis aims to explain the correlations between a set of observed variables with a set of smaller latent variables or factors (Fabrigar, Wegener, MacCallum & Strahan, 1999). Hence, the aim of the analysis was to identify and illuminate the nature of the non-observable sources of common variance that underlie responses to the items of the GWSS. Ideally, only one major source of common variance should be identified and it is hoped that this source will correspond to the construct of general work stress. However, the study is exploratory and aims to identify all noteworthy sources of common variance that underlie the responses to the items of the GWSS.

Factor analysts have developed a wide range of techniques that may be used to decide the number of factors to extract. Empirical investigations have shown that these techniques do not always point to the same number of factors and experts have recommended that analysts (a) consider the information provided by several techniques, and (b) make a final decision on the number of factors against the background of the theoretical meaningfulness and interpretability of the factors obtained (Preacher & MacCallum, 2003).

It is necessary to emphasise three points in regard to the number of factors problem that serve as background to the decisions that were made in this study. Firstly, there is no "true" number of factors to retain. Rather, the goal of the factor analysis is to identify the major factors that account for the correlations of the items. Secondly, it is better to extract too many rather than too few factors. Underextraction leads to distortion of the extracted factors. In contrast, overextraction generally does not distort the character of the major factors (Wood, Tataryn & Gorsuch, 1996). Thirdly, decisions about the number of factors should preferably be made against the background of the interpretability and psychological meaningfulness of the factors.

The following techniques and criteria were used to decide the number of factors to retain: (a) the chi square goodness of fit statistic, (b) inspection of the residual matrix, (c) the standardised root mean squared residual (SRMR), (d) the root mean square error of approximation (RMSEA), (e) eigenvalues > 1, (f) the scree plot, and (g) parallel analysis. Each of these techniques is described in more detail in the Appendix.

The correlations between first-order factors were subjected to a second-order maximum likelihood factor analysis, which was subsequently transformed to an orthogonal hierarchical structure where all the factors at all levels of the factor hierarchy are uncorrelated (Schmid-Leiman, 1957). This transformation allows for an unambiguous evaluation of the relative importance of the first-order and higher-order factors (Gorsuch, 1983).

The similarity of the factors obtained in the two independent samples was assessed by means of the coefficient of congruence (Tucker's phi). MacCallum, Widaman, Zhang and Hong (1999) offered the following guidelines for interpretation of the coefficient of congruence: 0.98 to 1.00 = excellent factor similarity, 0.92 to 0.98 = good similarity, 0.82 to 0.92 = borderline similarity; 0.68 to 0.82 = poor similarity; and below 0.68 = terrible similarity.

RESULTS

Maximum likelihood factor analysis proceeds on the assumption that the data have a multivariate normal distribution, which in turn implies that each individual variable is normally distributed. Violation of this assumption may lead to distorted factor analytic results. West and Curran (1995) suggested that the maximum likelihood method can produce useful results as long as the skewness of each observed variable is < 2,0 and the kurtosis is < 7,0. It can be seen from Table 1 that all the items of the GWSS meet these criteria for Groups 1 and 2.

Table 1
Descriptive statistics for the nine items of the GWSS

	Group 1 (n = 475)				Group 2 (n = 477)			
	M	SD	Skew ness	Kurtosis	M	SD	Skew-ness	Kurtosis
G1	2,66	1,12	0,01	-0,75	2,51	0,99	0,31	-0,12
G2	2,32	1,11	0,44	-0,58	2,01	1,00	0,82	0,15
G3	2,33	1,15	0,55	-0,57	1,89	0,93	0,87	0,37
G4	2,38	1,16	0,41	-0,82	2,17	1,05	0,48	-0,53
G5	2,15	0,94	0,51	-0,26	2,00	0,88	0,60	0,43
G6	2,21	0,97	0,42	-0,54	1,96	0,86	0,63	0,02
G7	2,71	1,10	0,14	-0,78	2,46	1,09	0,40	-0,50
G8	2,29	1,13	0,35	-1,01	1,69	0,88	1,06	0,44
G9	2,34	1,00	0,35	-0,43	2,05	0,96	0,67	-0,14

Factor analysis of Group 1 data

Maximum likelihood solutions with one, two and three factors were obtained. These models are labelled Model 1, Model 2 and Model 3, respectively. Inspection of Table 2 shows that the residual matrices of Model 1 [$\chi^2(27) = 337{,}469$, $p < 0{,}05$], Model 2 [$\chi^2(19) = 119{,}366$, $p < 0{,}05$], and Model 3 [$\chi^2(12) = 25{,}596$, $p < 0.05$] differed statistically significantly from zero. The ratio of the chi-square to the degrees of freedom of Model 3 was substantially lower than the corresponding ratios of Models 1 and 2, suggesting that Model 3 provides the best fit.

Table 2
Residual based indicators of the number of factors to retain

Model	SRMR	RMSEA	χ^2	df	χ^2/df
Group 1 (n = 475)					
1	0,070	0,155 (0,140; 0,170)	337,469	27	12,499
2	0,042	0,105 (0,087; 0,123)	119,366	19	6,282
3	0,013	0,049 (0,022; 0,075)	25,596	12	2,133
Group 2 (n = 477)					
1	0,050	0,112 (0,097; 0,127)	188,427	27	6,979
2	0,033	0,085 (0,067; 0,114)	85,037	19	4,476
3	0,015	0,044 (0,014; 0,071)	22,977	12	1,915

Note. The values in parenthesis represent the upper and lower limits of the 90% confidence interval around the point estimate of the RMSEA.

Model 1 produced 16 residuals ≥ 0,05, whereas Model 2 produced only four residuals ≥ 0,05. Model 2 clearly did a better job in accounting for the correlations of the nine items, but a relatively large correlation residual of 0,198 between items G4 and G7 remained. Model 3 did not produce any residuals ≥ 0,05 and the biggest absolute residual was only 0,027. The SRMR of Models 1, 2 and 3 were 0,070, 0,042, and 0,013, respectively (see Table 2). The SRMR of Model 3 was very small and the extraction of further factors did not appear warranted. The SRMR's of Models 1 and 2 were also relatively small, but these two models produced relatively large individual residuals (as was pointed out in the previous paragraph).

Table 2 also gives the RMSEA point estimates and corresponding 90% confidence intervals for Models 1, 2 and 3, respectively. The RMSEA point estimate of Model 1 was 0,155 with 90% confidence limits of 0,140 and 0,170, suggesting a weak fit between the model and the observed data. The RMSEA point estimate for Model 2 was 0,105. The lower limit of the 90% confidence interval was 0,087, which points to a mediocre fit, whereas the upper limit was 0,123, which points to a weak fit. Overall, the fit of Model 2 appears unsatisfactory. In contrast, Model 3 appears to fit the observed data well. The RMSEA point estimate was 0,049, which means that the hypothesis of a close fit cannot be rejected. The upper limit of the 90% confidence interval was 0,075, which suggests that the true fit between the model and the observed data is satisfactory.

In addition to the residual based factor retention criteria, we also considered criteria based on the eigenvalues of the intercorrelation matrix. The eigenvalues of the unreduced intercorrelation matrix were as follows: 5,202, 0,889, 0,742, 0,571, 0,427, 0,379, 0,314, 0,257, and 0,218. There was only one eigenvalue > 1, suggesting that only factor should be retained. Parallel analysis of the reduced intercorrelation matrix showed that three eigenvalues of the observed data were greater than the corresponding eigenvalues of the parallel random data, suggesting that three factors should be retained (see Figure 1) . Figure 1 also shows one clear "elbow" at the second root. Hence, the scree test suggests that one factor should be retained.

Table 3
Summary of the results of different indicators of the number of factors to extract

Indicator	Number of Factors	
	Group 1	Group 2
Eigenvalues > 1 (unreduced correlation matrix)	1	1
Scree plot (reduced correlation matrix)	1	1
Parallel analysis (reduced correlation matrix)	3	3
Root Mean Squared Residual (RMR)	3	3
Root Mean Square Error of Approximation (RMSEA)	3	3

Table 3 contains a summary of the results of the different indicators of the number of factors to extract. It appears that either one or three factors should be retained. Against the background that it is safer to overextract rather than to underextract (Wood et al., 1996), three factors were retained and obliquely rotated to the Promax (k = 4) criterion. Inspection of the factor pattern matrix (see Table 4) shows that each factor was well determined with at least three factor pattern coefficients > 0,30.

The factor structure matrix (see Table 5) and the factor correlation matrix (see Table 6) show that the three factors overlap substantially. The factor structure coefficients (which are correlations between the items and the factors) indicate that each item correlated moderately to strongly with each of the three factors. In addition, the correlations of the three factors ranged from 0,692 to 0,711, which point strongly toward the presence of a general factor.

Table 4
Oblique factor pattern matrix of the nine items of the GWSS (promax, k = 4)

	Group 1			Group 2		
	Factor 1	Factor 2	Factor 3	Factor 1	Factor 2	Factor 3
G1	0,952	-0,050	-0,062	0,768	0,030	0,012
G2	0,824	-0,017	0,084	0,989	-0,062	-0,085
G3	0,740	0,087	0,011	0,613	-0,002	0,128
G4	0,127	-0,036	0,744	0,144	-0,038	0,662
G5	0,003	0,839	-0,031	-0,074	0,959	-0,046
G6	0,041	0,852	-0,003	0,226	0,533	0,091
G7	-0,074	0,003	0,814	-0,078	0,011	0,873
G8	0,092	0,382	0,357	0,487	0,190	0,134
G9	0,491	0,140	0,026	0,167	0,246	0,243

Note. All factor pattern coefficients > 0,30 are underlined.

Table 5
Oblique factor structure matrix of the nine items of the GWSS (promax, k = 4)

	Group 1			Group 2		
	Factor 1	Factor 2	Factor 3	Factor 1	Factor 2	Factor 3
G1	0,874	0,565	0,576	0,798	0,586	0,592
G2	0,872	0,613	0,655	0,883	0,581	0,590
G3	0,808	0,607	0,596	0,705	0,526	0,573
G4	0,628	0,581	0,809	0,599	0,537	0,740
G5	0,562	0,819	0,567	0,575	0,874	0,584
G6	0,628	0,878	0,631	0,671	0,759	0,635
G7	0,504	0,531	0,764	0,564	0,578	0,824
G8	0,609	0,700	0,694	0,719	0,632	0,623
G9	0,606	0,498	0,473	0,519	0,538	0,540

Note. All factor structure coefficients > 0,30 are underlined.

Table 6
Intercorrelations of the first order factors of the GWSS

Factor	1	2	3
1	1,000	0,712	0,727
2	0,692	1,000	0,713
3	0,707	0,711	1,000

Note. Correlations below the diagonal are for Group 1, Correlations above the diagonal are for Group 2

In view of the overlap of the three factors, a higher-order factor solution with a single second-order factor was obtained. This solution was transformed to an orthogonal Schmid-Leiman (1957) hierarchical factor solution, which produced a single second-order factor and three group or primary factors, where all the factors at all hierarchical levels are uncorrelated (see Table 7). This transformation allows for a clear evaluation of the relative influences of factors at different levels of the factor hierarchy (McDonald, 1999).

Table 7
Hierarchical Schmid-Leiman factor solution for the items of the GWSS (group 1)

	S	P1	P2	P3	h^2
G1	0,696	0,532	-0,028	-0,032	0,768
G2	0,741	0,460	-0,009	0,044	0,763
G3	0,696	0,413	0,048	0,006	0,658
G4	0,709	0,071	-0,020	0,389	0,660
G5	0,676	0,002	0,463	-0,016	0,671
G6	0,742	0,023	0,470	-0,002	0,772
G7	0,635	-0,041	0,002	0,426	0,586
G8	0,699	0,051	0,211	0,187	0,571
G9	0,546	0,274	0,077	0,014	0,380
% shared variance	72,4	12,9	8,4	6,4	

Note. S = higher order factor, P = primary or group factor. Factor pattern coefficients that define the factor corresponding to a particular column are underlined.

It can be seen from Table 7 that the Schmid-Leiman transformation produced one well defined second-order factor and three relatively weakly defined group factors. Each of the nine items had its highest factor pattern coefficient on the second-order factor, and all these coefficients were moderately strong to strong. In comparison, the three group factors were less clearly defined. Inspection of the items that loaded on the three group factors suggest that the factors might be labelled (a) desire to work at another place (items G1, G2, and G3), (b) impaired concentration (items G5 and G6), and (c) tendency to worry (items G4 and G7).

The second-order factor accounted for 72.4% of the shared variance of the nine items, whereas the three group factors accounted for only 12.9%, 8.4% and 6.4%, respectively. This result shows that responses to the items of the GWSS are dominated by the general factor and that in comparison the group factors have a relatively minor influence.

Factor analysis of Group 2 data

Overall, the results obtained with the data of Group 2 appear very similar to the results obtained with the data of Group 1. The chi-square goodness of fit statistic for all three models was statistically significant (see Table 2), but the SRMR, RMSEA, and parallel analysis pointed toward the retention of three factors. The factor structure matrix (see Table 5) and the factor correlations resulting from a Promax rotation (see Table 6), again strongly suggest the presence of a general factor. A higher-order factor was extracted and the Schmid-Leiman transformed hierarchical factor solution is given in Table 8.

The general factor accounted for 74.7% of the shared variance, and the three group factors for 11,6%, 7,2%, and 6,6%, respectively. This result is very similar to that for the first data set and shows that the influence of the general factor is large relative to the influence of the group factors.

The coefficients of congruence for the corresponding factors of the two groups were as follows: General factor, Tucker's phi = 0.999; Group factor 1, Tucker's phi = 0.920; Group factor 2, Tucker's phi = 0.943; and Group factor 3, Tucker's phi = 0.939. These results show that the general factor manifests almost identically across the two data sets, whereas the similarity of the group factors across the two samples can be described as "good".

Table 8
Hierarchical Schmid-Leiman factor solution for the items of the GWSS (group 2)

	S	P1	P2	P3	h²
G1	<u>0,690</u>	<u>0,403</u>	0,006	0,016	0,638
G2	<u>0,718</u>	<u>0,519</u>	-0,044	-0,034	0,788
G3	<u>0,630</u>	<u>0,321</u>	0,067	-0,001	0,504
G4	<u>0,656</u>	0,076	<u>0,346</u>	-0,021	0,556
G5	<u>0,699</u>	-0,039	-0,024	<u>0,526</u>	0,768
G6	<u>0,716</u>	0,119	0,048	<u>0,292</u>	0,614
G7	<u>0,687</u>	-0,041	<u>0,456</u>	0,006	0,682
G8	<u>0,688</u>	0,255	0,070	0,104	0,554
G9	<u>0,555</u>	0,088	0,127	0,135	0,350
% shared variance	74,7	11,6	6,6	7,2	

Note. S = higher order factor, P = primary or group factor. Factor pattern coefficients that define the factor corresponding to a particular column are underlined.

As a last step we calculated McDonald's coefficient omega, which represents the square of the correlation between the total score and the general factor that underlies responses to the items (McDonald, 1999). For Group 1 omega was 0.831, whereas for Group 2 omega was 0.833. Taking the square root of omega shows that the correlations between the total score and the general factor, which might also be interpreted as representing the domain from which the items of the GWSS was drawn, is 0.911 and 0.913 for the two groups, respectively.

DISCUSSION

The goal of this study was to examine the dimensionality or factor structure of the GWSS. A variety of residual based and eigenvalues based criteria were employed to decide the number of factors to retain. Across two independent data sets it appeared that a correlated three factor solution provides the best fit to the observed data. These factors appear to represent (a) a motivational disruption dimension reflected by a desire to work at another place, (b) a cognitive disruption dimension reflected by concentration and attentional difficulties, and (c) an affective disruption dimension reflected by a tendency to worry about work. It should be noted at this point that the GWSS was designed to function as a unidimensional scale of work stress. Hence, at first glance the finding of three dimensions or factors of felt work stress appears to run counter to the model on which the scale is based.

However, second-order factor analyses with a hierarchical Schmid-Leiman (1957) transformation showed that responses to the items are dominated by a general factor and that in comparison the influence of the three group factors is relatively weak. Across the two samples, the general factor accounted for at least six times more shared variance than any particular group factor. From this perspective, it appears justified to compute a single total score for the GWSS. McDonald's coefficient omega showed that this total score is very strongly correlated with the hypothetical domain of which the items are a subset, which provides support for the construct validity of the total score. At this stage it appears unwise to obtain scores for the three group factors because they (a) are defined by very few items, (b) represent narrow constructs of possibly limited psychological importance, and (c) need further replication.

One may ask whether the extraction and subsequent rotation of three factors rather than one, as was suggested by the eigenvalues > 1 criterion and the scree test, was worth the effort. The substantive conclusion, namely that it is justified to obtain a total score for the GWSS would have been the same if only one factor was extracted. However, the extraction of three factors, and the subsequent hierarchical transformation of the factors, provided a detailed and finely grained picture of the sources of common variance that underlie responses to the items of the GWSS. From a theoretical perspective, the extraction of three factors afforded deeper insight into the constructs that the GWSS measures. From a content validity perspective, it is reassuring to note that motivational, affective, and cognitive manifestations of work related stress are covered by the items of the GWSS.

The extraction of three factors also afforded useful clues as to how the GWSS may be improved. These insights would not have been gained if only one factor was extracted. The three group factors point to the presence of minor local dependencies among the items of the GWSS. In regard to the first group factor, it appears that item G1 ("Does work make you so stressed that you wish you had another job?") and item G2 ("Do you get so stressed at work that you want to quit?") overlap in content, which produces a local dependency. Similarly, in regard to the second group factor, item G5 ("Do you get so stressed at work that you forget to do important tasks?") and item G6 ("Does work make you so stressed that you find it hard to concentrate on your tasks?") overlap in content. Finally, in regard to the third group factor, item G4 (Do you find it difficult to sleep at night because you worry about your work?) and item G7 (Do you spend a lot of time worrying about your work?) also overlap in content.

The GWSS might be improved by revising some items so that there is less content overlap. This might be especially fruitful in regard to the first group factor, which accounted for the most residual variance. Alternatively, the observed local dependencies may be viewed as the seeds for the development of a multidimensional scale of subjectively experienced work stress. The three group factors might be developed further into scales by writing additional items to represent each of the factors. This would allow for a detailed multidimensional examination of how an individual experiences stress.

Overall, the results show that the GWSS shows promise as a measure of felt or subjectively experienced stress in the workplace. The scale may be used as an indicator of the level of psychological discomfort that an individual experiences as a result of his or her appraisal of stressors in the workplace. Although the scale is based on a transactional perspective of stress, it may also be used as an intervening or outcome variable by investigators working from an environmental perspective. In such a case scores on the scale may be seen to reflect experienced levels of stress as a result of being exposed to inherently stressful events or situations, such as excessive workloads, role ambiguity, and low job control. Hence, the GWSS is a flexible tool that may be used as an indicator of felt stress regardless of the theoretical framework that an investigator adopts. Felt stress or subjectively experienced work stress, as measured by the GWSS especially holds promise as a variable that intervenes between exposure to job demands and job strain outcomes. From this perspective, it is the subjective experience of stress that leads to undesirable outcomes such as burnout, low satisfaction, absenteeism, turnover, and poor health (Summers, et al., 1995).

In conclusion, the results provide support for the construct validity of the GWSS. As expected, a single dimension or general factor dominated the responses to the items and it appears that researchers may safely compute a total score to represent respondents' general work stress. This score represents an individual's level of subjectively experienced or felt stress and is the result of an individual's appraisal that the demands of the working environment exceed his or her resources to meet the demands. Three minor group factors of subjectively experienced stress were identified, but these factors are largely due to some content overlap and appear to have a trivial influence. Future revisions of the scale may focus on eliminating these group factors through the rewording of some items.

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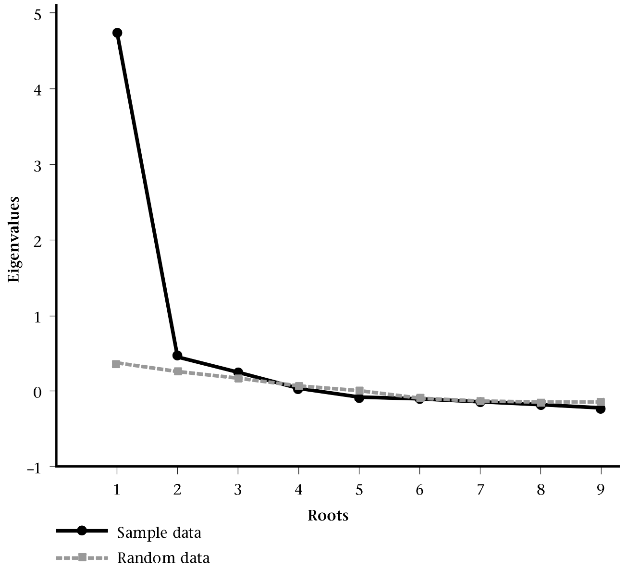

Figure 1. Scree plot and parallel analysis plot for Group 1

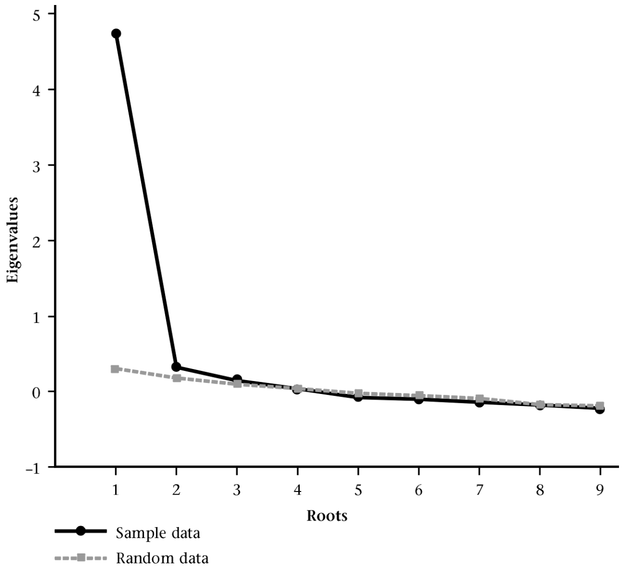

Figure 2. Scree plot and parallel analysis plot for Group 2

APPENDIX

Visual inspection of the residual matrix

The correlation residuals provide the most direct indication of the degree to which a given number of factors have succeeded in accounting for the correlations of a set of observed variables. One guideline is that the extraction of factors can be discontinued when the majority of the residuals are < 0,10 (McDonald, 1999).

The standardised root mean squared residual

The standardised root mean squared residual serves as a summary index of the average size of the residuals in the residual matrix. A small SRMR shows that the given number of factors gives a satisfactory account of the correlations between the observed variables, whereas a large SRMR shows that more factors should be extracted. A guideline is that a SRMR < 0,08 indicates that the factors give a satisfactory account of the observed correlations. The SRMR can also be used to compare factor solutions with different numbers of factors. The SRMR necessarily decreases with the extraction of each successive factor, but when the improvement in the SRMR becomes very slight, it serves as a clue that factor extraction may be discontinued.

Statistical significance of the residual matrix

Modern methods of factor analysis, of which maximum likelihood factor analysis appears to be the most popular, estimates factor loadings so that a given function of the residuals is at a minimum (McDonald, 1999). The function to be minimised is called the discrepancy function, F. In the maximum likelihood method the residuals are conceptualised as the discrepancy between the reproduced correlation matrix and the corresponding population correlation matrix. Because the population correlation matrix is unavailable, the observed correlation matrix is used as a substitute.

The hypothesis that the residual matrix is a zero matrix is tested with a chi-square statistic. A significant chi-square shows that the residuals differ from zero and that the chosen number of factors does not give a perfect account of the correlations of the observed variables. In contrast, a non significant chi-square shows that the hypothesis of a perfect fit between the chosen number of factors and the observed correlation matrix can not be rejected.

A disadvantage of the chi-square is that it is very sensitive to the effect of sample size. With a big sample trivial residuals may produce a significant chi-square, whereas with a small sample large residuals may go undetected. Several authors have argued that the chi-square is inappropriate because it is a test of perfect fit and it is unrealistic to expect any given number of factors to perfectly account for the correlations of a set of observed variables. From this perspective it is more reasonable to require of a factor solution to give a satisfactory account of the correlations. For this reason the chi-square test of a perfect fit is not widely recommended as a test of the number of factors.

Root Mean Square Error of Approximation

The RMSEA (Steiger & Lind, 1980) is an increasingly popular index of the number of factors to extract. The RMSEA represents the discrepancy between the observed and reproduced correlation matrices per degree of freedom:

$$RMSEA = \sqrt{\frac{F}{df}}$$

where F = the discrepancy function, and df = the degrees of freedom (Browne & Cudeck, 1992). Smaller values of the RMSEA point to a better fit between the chosen number of factors and the observed data. An attractive feature of the RMSEA is that it only decreases if the extraction of an additional factor leads to a substantial reduction in the discrepancy function. In fact, the RMSEA can increase if the extraction of an additional factor (and therefore also a loss in degrees of freedom) leads only to a trivial reduction in the discrepancy function. Hence, the RMSEA rewards an optimal balance between minimisation of the discrepancy function and the complexity of the factor model. From this perspective, the RMSEA is congruent with the goal of explaining as much of the variance in the intercorrelation matrix as possible with as few factors as possible (Browne & Cudeck, 1992).

A RMSEA point estimate equal to zero indicates a perfect fit between the factor model and the observed data. Browne and Cudeck (1992) recommended that a RMSEA point estimate < 0,05 indicates a close fit, whereas a point estimate > 0,05 but < 0,08 indicates a satisfactory fit. A point estimates > 0,10 indicates a weak fit. One can also construct 90% confidence intervals around the RMSEA point estimates. A wide confidence interval shows that the RMSEA point estimate is a relatively imprecise indicator of fit in the population, whereas a narrow confidence interval shows that the point estimate is a relatively precise indicator of fit in the population.

Eigenvalues-greater- than-one-criterion

The eigenvalues-greater-than-one-criterion is perhaps the most widely used criterion in regard to the number of factors to extract. A common interpretation is that one should extract as many factors as there are eigenvalues > 1 in the unreduced observed intercorrelation matrix. The criterion, which is also known as the Kaiser criterion, reflects the idea that factors with eigenvalues < 1 explain less variance than a single standardised observed variable (Zwick & Velicer, 1986).

Scree test and parallel analysis

Parallel analysis is based on the rationale that factors worth retaining should account for more variance than can be attributed to chance alone (Horn, 1965). The procedure requires that the eigenvalues of the reduced correlation matrix (with communalities in the main diagonal) and the eigenvalues of parallel random data be jointly plotted against the roots. Only factors with actual eigenvalues greater than the eigenvalues of the parallel random data set should be retained (Hayton, Allen & Scarpello, 2004).

The plot of the eigenvalues of the reduced intercorrelation matrix may also be used to implement the scree test (Cattell, 1966), which is based on the rationale that if there are m important factors, there should be m relatively large eigenvalues. Typically, the differences between the successive eigenvalues are relatively large for the first few factors, after which the differences taper off. On the scree plot this can usually be seen as a relatively steep descending slope to the lower right of the plot, until an “elbow” or break point is reached after which the slope gradually tapers off to the lower right. The scree test dictates that factors that lie above the “elbow” are the factors that should be retained. Factors that lie at or below the breakpoint are considered unimportant (Hayton et al., 2004).