An initial review of the structure of the Westerman Aboriginal Symptom Checklist – Adults (WASC-A) using Structural Equation Modelling (SEM) BY CHRIS BRIGHT BPsych (HONS) GradCertFac MAppPsych

To confirm the theoretical structure of the WASC-A, confirmatory factor analysis (CFA) was undertaken using structured equation modelling (SEM). CFA was chosen because it is considered the appropriate technique for establishing construct validity (Floyd and Widaman as cited in Bodin, Pardini, Burns, & Stevens, 2009) as it allows specific measures of a construct to be tested and to evaluate whether they are consistent with theoretical assumptions (Boomsma, 2000; Chilcot et al., 2011). The current study used Maximum Likelihood Estimation (MLE) as the SEM estimation procedure and was undertaken using AMOS 19 software (Arbuckle, 2010).

The procedure for undertaking SEM to examine the WASC-A, including guidelines for interpretation and reporting of results, is consistent with those described in the literature (see Boomsma, 2000; Hair, Black, Babin, & Anderson, 2010; Jackson, Gillaspy, & Purc-Stephenson, 2009). The procedure for conducting SEM occurs in three distinct phases:

i) Data Preparation and Screening

ii) Estimation Procedures – Determining the Goodness-of-Fit of the model

iii) Assessing the Measurement model – Determining Construct Validity and Reliability

Data preparation and screening procedures were undertaken prior to conducting SEM. This is particularly important as SEM is sensitive to violations of assumptions. Consistent with Tabachnick and Fidell's (2001) guidelines, missing data, normality, outliers and multi-collinearity were considered for the dataset.

The Missing Value Analysis procedure of SPSS 19.0 was used to examine for missing data in the original sample size of 392 respondents. The EM (expectation-maximization) algorithm determined that missing data in the sample were not missing completely at random. As it is unsafe to impute missing values for a final report of results, and because estimates derived from other missing value methods (e.g. listwise, pairwise, regression) will be biased (SPSS Inc., 2007), respondents with missing data were culled from the dataset, thereby reducing the working sample size to 370. In SEM, sample size plays a significant role in the reliability of outcomes (Teo, Luan, & Sing, 2008). The sample size of 370 is considered suitable for this research methodology (Addington, Girard, Christensen, & Addington, 2010; Kenny, 2011) as it balances the various considerations when conducting SEM such as multivariate normality of data, model complexity, missing data, etc. (Hair et al. 2010).

The current study used the Maximum Likelihood estimation method which assumes multivariate normality. No evidence of skewness or kurtosis issues were identified in the sample, and univariate and multivariate outliers were not detected. However consideration of a bivariate correlation matrix did indicate the presence of multicollinearity (i.e. correlations ≥ .85) between certain items in the current data set. These high correlations occurred between items on the Suicide subscale (see Table 1) and the Alcohol and Drug subscale (see Table 2). Given the foci of these questions, the presence of high correlations is not surprising and does not necessarily indicate similar content between items. Consideration of these items indicated that only items q25 and q26 were similar in content and in turn q26 was not included in the SEM undertaken for the Alcohol and Drug subscale.

Table 1: Suicide Subscale Correlations ≥ .85

	q12 I have felt so sad I have thought about ending my life	q14 I have planned how I would end my life
q13 When I have had these thoughts I find it hard to stop them	.882 **	.888 **

***p* < .001

Table 2: Alcohol and Drug Subscale Correlations ≥ .85

	q25 When I drink or use drugs, I often use or drink more than I intend to	q26 When I have a drink or use drugs I find it hard to stop myself	q27 When I am drunk or high, I do things I feel real shame about the next day	q28 My alcohol or drug use has had a bad impact on me (health, family, work)
q24 I drink grog smoke gunja or use other drugs	.872 **	.867 **		
q25 When I drink/ use drugs, I often use/ drink more than I intend to		.995 **	.908 **	.936 **
q26 When I have a drink/ use drugs I find it hard to stop myself			.905 **	.934 **
q27 When I am drunk/ high, I do things I feel real shame about the next day				.927 **

***$p < .001$

Estimation Procedures - Determining the Goodness-of-Fit of the model

Structural equation modelling (SEM) was performed to test the fit between the hypothesized factor structure as presented in Table 3 and the obtained data. To test the goodness-of-fit of the WASC-A a variety of indices were considered in line with best practise (Byrne, 2010; Hair et al., 2010; Roberts, 1999; Sawang et al., 2010). The indices used to assess the fit of the WASC-A included the following:

- x^2 (CMIN) and *p*-value,
- Relative x^2/df (CMIN/DF),
- Standardised Root Mean Square Residual (SRMR),
- Goodness-of-Fit Index (GFI),
- Tucker-Lewis Index (TLI),
- Bentler's Comparative Fit Index (CFI),
- Root Mean Square of Approximation (RMSEA) with 90% confidence interval (CI) and *p*-value (PCLOSE).

A summary of threshold criteria for goodness-of-fit indices is provided below in Table 3.

Table 3 Summary of threshold criteria for Goodness-of-Fit indices

x^2 (CMIN)	Low x^2 values which support that the model is representative of the data (Hair et al. 2010). Note: Problematic as a goodness-of-fit measure as it is bias against large samples and increased model complexity, hence alternative measures of fit are referred to also.
p-value	Non-significant probability cannot reject the goodness-of-fit of the hypothesized model (Byrne 2010)
x^2/ df	Ratio of less than 2 indicates a good-fitting model (Tabachnick & Fidell 2001), although between 2 and 5 is acceptable (Paswan 2009, Shumacker and Lomax as cited in Sawang, Oei et al. 2010)
SRMR	Value approaching 0 indicates a good-fitting model (Hair et al. 2010)
GFI	Required value of >.9 for this index (Tabachnick & Fidell 2001)
TLI, CFI	Required value of between > .9 (Tabachnick & Fidell 2001) and ≥.95 (Hair et al. 2010)
RMSEA	Value of .10 or less is considered acceptable (Paswan 2009). Desired value of ≤.08 (Tabachnick & Fidell 2001)
PCLOSE	Desired value of >.05 and non-significant (Jöreskog & Sörbom as cited in Byrne 2010)

Assessing the Factor Loading and Sample Size

In addition to considering goodness-of-fit indices, the factor loadings for the items of each subscale were also considered. Factor loadings are important to consider as the larger the absolute size of the factor loading, the more important in interpreting the factor matrix. In other words, the larger an item's factor loading on its subscale factor (over a minimum level), the more the item is said to "explain" that factor.

Hair et al. (2010) define factor loadings as the correlation between the original items and the factors, and the key to understanding the nature of a particular factor. Squared factor loadings (also known as squared multiple correlations) indicate what percentage of the variance in the original item is explained by the factor. As such, a .30 factor loading translates to approximately 10 percent of the variance being accounted for by the factor, a .50 loading denotes about 25 percent explanation, and so on.

Hair et al. (2010) advises that when practical significance is the criteria and the sample size is 100 or larger, factor loadings in the range of ±.30 to ±.40 are considered to meet the minimal level for interpretation of structure, with loadings of ±.50 or greater being considered as practically significant. When statistical significance is the criteria, the minimum desired factor loading differs for different sample sizes (Hair et al. 2010). Table 4 indicates the sample sizes necessary for each factor loading value to be considered significant. In the current sample which had a sample size of 370, the minimum factor loading that is acceptable in terms of statistical significance is .30.

Table 4: Guidelines for identifying significant factor loadings based on sample size

Factor Loading	Sample Size
.30	350
.35	250
.40	200
.45	150
.55	100
.75	50

Adapted from Hair et al. (2010)

This significance is based on a .05 significance level, a power level of 80 percent, and standard errors assumed to be twice those of conventional correlation coefficients.

Assessing the WASC-A scales

The WASC-A is hypothesized to have six subscales. Table 5 provides a summary of the subscales and their related items.

Table 5: WASC-A Subscales and related Items

Subscale	Items
Depression	q1-q11
Suicide	q12-q23
Alcohol and Drug	q24-q28
Impulsivity	q29-q31
Anxiety	q32-q42
Cultural Resilience	q43-q57

To determine if these subscales provide a good fit to the data, the subscales were examined separately and are described below.

Depression Subscale

It was hypothesized that 11 items (q1 – q11) loaded on the Depression subscale. Goodness-of-fit for this model is presented in Table 6 and indicates a good fit to the data. Examination of standardised residual values and modification indices (MIs) did not identify values worth noting and as such no further improvements to the model were undertaken.

Table 6 Depression Goodness-of-Fit Indices

	x^2(df)	p-value	x^2/df	SRMR	GFI	TLI	CFI	RMSEA	90%CI	PCLOSE
One Factor Model	89.66 (44)	.00	2.04	.04	.96	.94	.96	.05	.04, .07	.36

All factor loadings were acceptable and were significant (p<.05). Factor loadings and squared multiple correlations are presented in Table 7.

Table 7: Depression Items' Factor Loadings & Squared Multiple Correlations

Item	Factor Loading	Squared Multiple Correlations
q1	.70	.49
q2	.53	.28
q3	.68	.46
q4	.35	.12
q5	.59	.35
q6	.57	.33
q7	.52	.27
q8	.64	.41
q9	.52	.27
q10	.66	.44
q11	.44	.19

Good construct reliability was observed for this model with a value of .84 indicating very good internal consistency. However, convergent validity was low as indicated by an average variance extracted value of .33. Overall, the findings provide very good support for the Depression factor. As presented in Figure 1, a final model for Depression included eleven items.

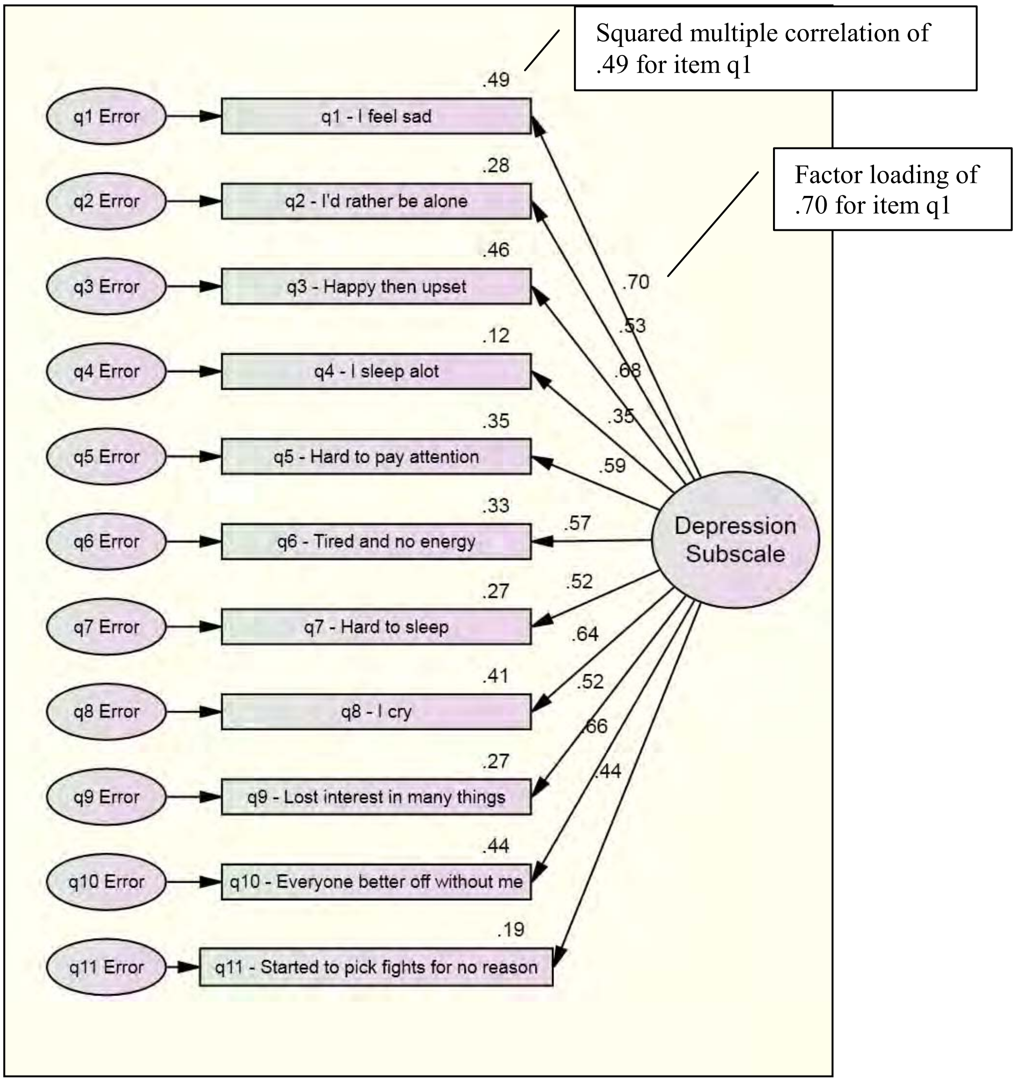

Figure 1: One factor model for Depression Subscale

Suicide Subscale

It was hypothesized that 12 items (q12-q23) loaded on the Suicide Subscale. However, items q16 (I have tried to end my life before) and q19 (I know someone who ended their life) were not included in model testing as they comprised a true/false answer format which does not lend itself to SEM. Initial model testing indicated two items worth further consideration. Item q21 (I feel like my life is getting worse and worse) was highlighted by modification indices as being a parameter that did not directly relate to the Suicide subscale although it influences and is influenced by the other items on this subscale. Item q23 (I look forward to the future) had a low factor loading (.08) and squared multiple correlation (.01) which do not explain a respectable portion of the variance in the Suicide Subscale. Consequently these items were removed from model testing. Further examination of standardised residual values and MIs did not identify other values worth noting and as such no further improvements to the model were undertaken.

Goodness-of-fit for a model (minus q16, q19, q21 and q23) is presented in Table 8 and indicates an overall good fit to the data. The final model presented in Figure 2 is considered to be the best fit to the data.

Table 8 Suicide Goodness-of-Fit Indices

	x^2(df)	p-value	x^2/df	SRMR	GFI	TLI	CFI	RMSEA	90% CI	PCLOSE
One Factor Model	110.05 (20)	.00	5.50	.02	.92	.96	.97	.11	.09, .13	.00

All factor loadings were acceptable and were significant (p<.05). Factor loadings and squared multiple correlations are presented in Table 9.

Table 9: Suicide Items' Factor Loadings & Squared Multiple Correlations

Item	Factor Loading	Squared Multiple Correlations
q12	.89	.79
q13	.95	.90
q14	.94	.88
q15	.88	.77
q17	.89	.78
q18	.89	.79
q20	.55	.31
q22	.45	.20

Very good construct reliability was observed for this model with a value of .94 indicating excellent internal consistency. Convergent validity was also good as indicated by an average variance estimate of .68. Overall, the findings provide support for the Suicide factor. As presented in Figure 2, a final model for Suicide included eight items.

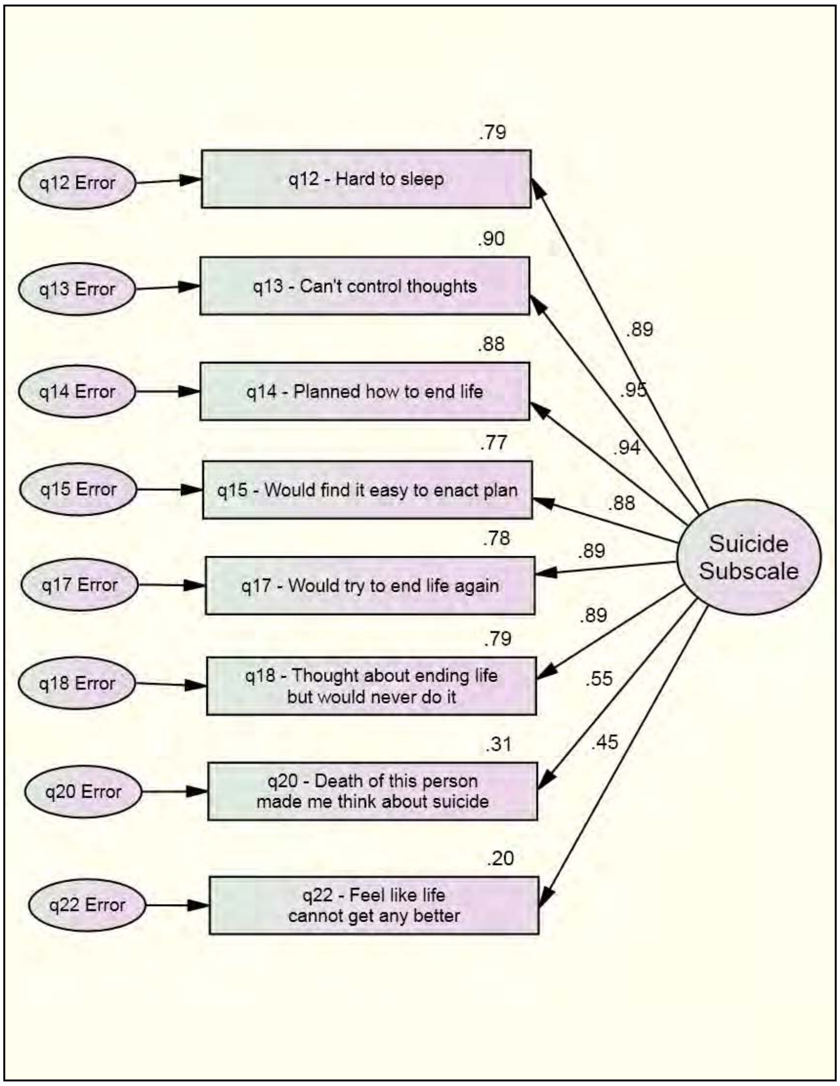

Figure 2: One factor model for Suicide Subscale

Alcohol and Drug Subscale

It was hypothesized that five items (q24 – q28) loaded on the Alcohol and Drug Subscale. Due to the high bivariate correlations between items in this subscale, consideration of the wording of items was undertaken to identify items with similar content. Items q25 (When I drink or use drugs, I often drink or use drugs more than I intend to) and q26 (When I have a drink or use drugs I find it hard to stop myself) were found to be similar. As a result item q26 was not included in model testing in this instance.

Goodness-of-fit for a model minus q26 is presented in Table 10 and indicates a good fit to the data. Examination of standardised residual values and MIs did not identify values worth noting and as such no further improvements to the model were undertaken.

Table 10 Alcohol and Drug Subscale Goodness-of-Fit Indices

	x^2(df)	p-value	x^2/df	SRMR	GFI	TLI	CFI	RMSEA	90% CI	PCLOSE
One Factor Model	29.02 (2)	.00	14.51	.01	.96	.96	.99	.19	.13, .26	.00

All factor loadings were acceptable and were significant (p<.05). Factor loadings and squared multiple correlations are presented in Table 11.

Table 11: Alcohol and Drug Items' Factor Loadings & Squared Multiple Correlations

Item	Factor Loading	Squared Multiple Correlations
q24	.88	.77
q25	.97	.93
q27	.95	.89
q28	.97	.94

Very good construct reliability was observed for this model with a value of .97 indicating very good internal consistency. Convergent validity was also very good as indicated by an average variance extracted value of .89. Overall, the findings provide very good support for the Alcohol and Drug factor. As presented in Figure 3, a final model for Alcohol and Drug included four items.

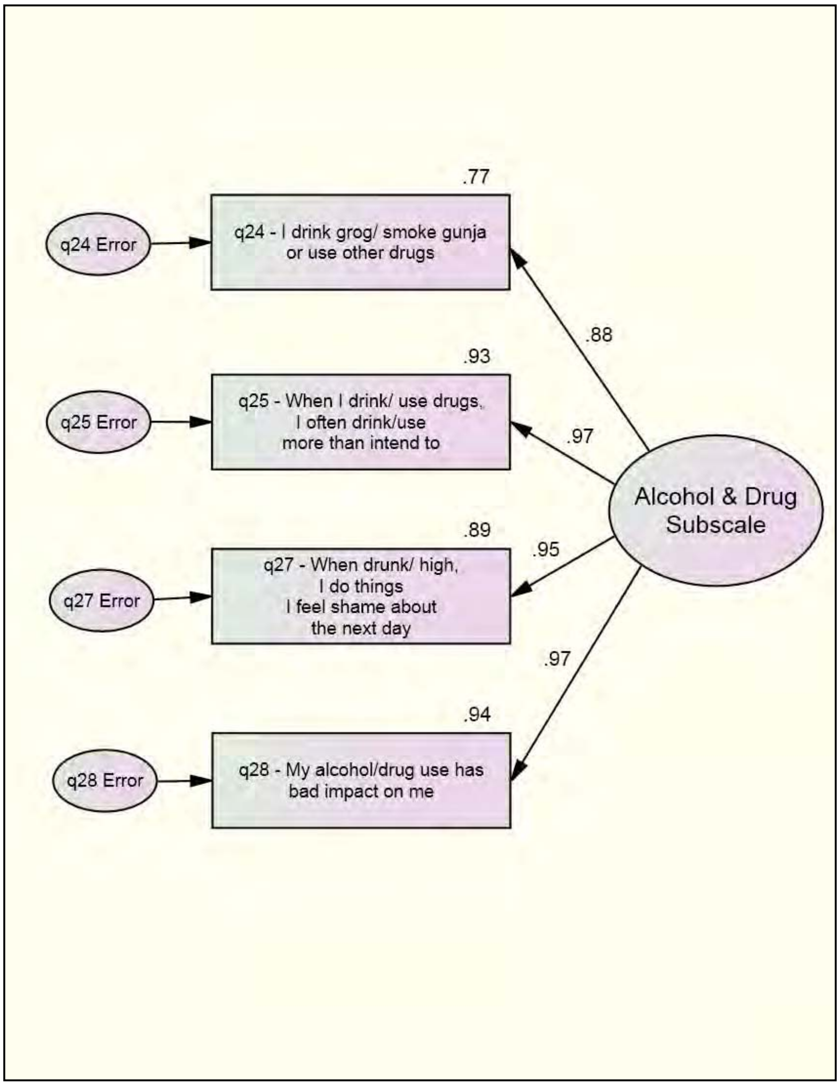

Figure 3: One factor model for Alcohol and Drug Subscale

Impulsivity Subscale

It was hypothesized that three items (q29 - q31) loaded on the Impulsivity subscale. Goodness-of-fit indices for the Impulsivity subscale were unable to be calculated as the model is considered to be "just-identified" (Szaflarski et al., 2006). A just-identified model has no degrees of freedom and therefore can never be rejected. As such, a goodness of fit evaluation does not apply (Brown, 2006) and the criterion of good fit is not statistical. Instead goodness-of-fit hinges on theoretical expectations, more specifically whether the loadings are the size one would expect given the logic of the model (Szaflarski et al., 2006).

In the case of the Impulsivity subscale, all factor loadings were reasonable to moderately high and were significant ($p<.05$) indicating a good fit. Factor loadings and squared multiple correlations are presented in Table 12.

Table 12: Impulsivity Items' Factor Loadings & Squared Multiple Correlations

Item	Factor Loading	Squared Multiple Correlations
q29	.51	.26
q30	.68	.46
q31	.82	.67

Good construct reliability was observed for this model with a value of .72 indicating very good internal consistency. Convergent validity was adequate as indicated by an average variance extracted value of .47. Overall, the findings provide support for the Impulsivity factor. As presented in Figure 4, a final model for Impulsivity included three items.

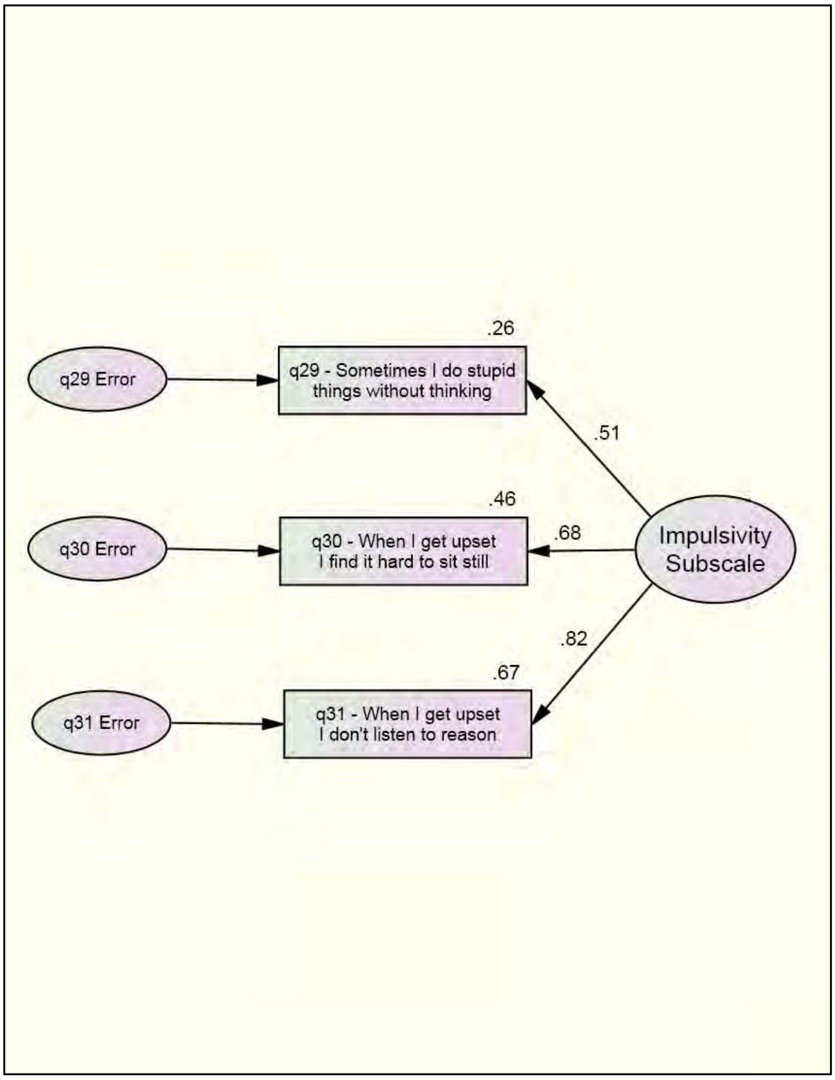

Figure 4: One factor model for Impulsivity Subscale

Anxiety Subscale

It was hypothesized that 11 items (q32 – q42) loaded on the Anxiety Subscale. However, initial model testing indicated that item q39 (When I worry about something I become all sweaty) had a low factor loading (.18) and squared multiple correlation (.03) which do not explain a respectable portion of the variance in the Anxiety Subscale. This item was removed from further model testing.

Goodness-of-fit for a model minus q39 is presented in Table 13 and indicates a good fit to the data. Examination of standardised residual values and modification indices did not identify values worth noting and as such no further improvements to the model were undertaken.

Table 13: Anxiety Goodness-of-Fit Indices

	x^2(df)	p-value	x^2/ df	SRMR	GFI	TLI	CFI	RMSEA	90% CI	PCLOSE
One Factor Model	82.164 (35)	.000	2.348	.0390		.945	.958	.060	.044, .077	.146

All factor loadings were acceptable and were significant (p<.05). Factor loadings and squared multiple correlations are presented in Table 14.

Table 14: Anxiety Items' Factor Loadings & Squared Multiple Correlations

Item	Factor Loading	Squared Multiple Correlations
q32	.58	.33
q33	.71	.51
q34	.64	.41
q35	.64	.41
q36	.70	.48
q37	.62	.38
q38	.60	.37
q40	58	.34
q41	.68	.46
q42	.36	.13

Good construct reliability was observed for this model with a value of .86 indicating very good internal consistency. Convergent validity was low as indicated by an average variance extracted value of .38. Overall, the findings provide very good support for the Anxiety factor. As presented in Figure 5, a final model for Anxiety included ten items.

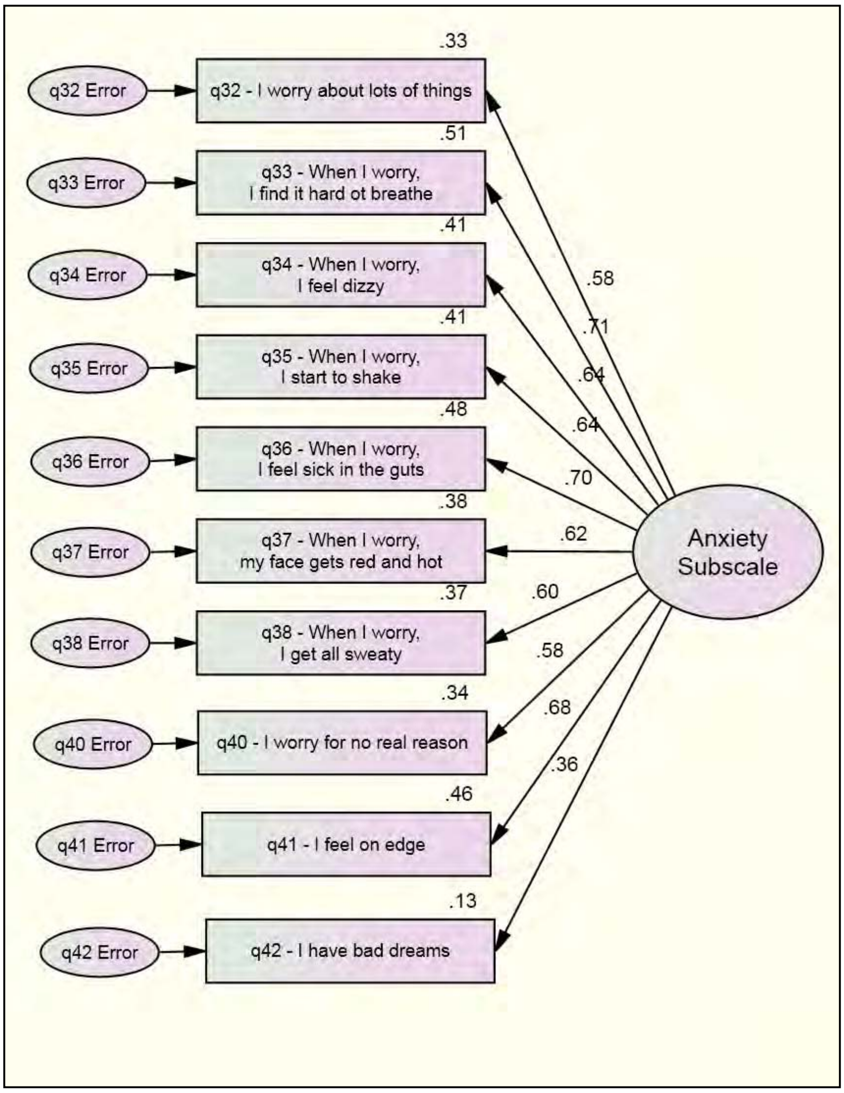

Figure 5: One factor model for Anxiety Subscale

Cultural Resilience Subscale

It was hypothesized that 15 items (q43 – q57) loaded on the Cultural Resilience Subscale. However, initial model testing indicated that items q50 (I speak my Aboriginal language) and q57 (There is someone I know who I can talk to) had low factor loadings (.09 and -.22 respectively) and low squared multiple correlations (.01 and .05 respectively), which suggests that they do not explain a respectable portion of the variance in the Cultural Resilience Subscale. These items were removed from further model testing.

Goodness-of-fit for a model minus q50 and q57 is presented in Table 15 and indicates an acceptable fit to the data. The Relative Chi-Square (x^2/ df) and the GFI can be considered as acceptable and similarly the RMSEA is also reasonable.

Table 15: Cultural Resilience Goodness-of-Fit Indices

	x^2(df)	p-value	x^2/ df	SRMR	GFI	TLI	CFI	RMSEA	90% CI	PCLOSE
One Factor Model	244.17 (65)	.00	3.76	.06	.91	.79	.82	.09	.07, .10	.00

All factor loadings were acceptable and were significant ($p<.05$). Factor loadings and squared multiple correlations are presented in Table 16.

Table 16: Cultural Resilience Items' Factor Loadings & Squared Multiple Correlations

Item	Factor Loading	Squared Multiple Correlations
q43	.36	.13
q44	.51	.26
q45	.57	.32
q46	.62	.39
q47	.57	.32
q48	.47	.22
q49	.47	.22
q51	.39	.15
q52	.44	.19
q53	.35	.12
q54	.57	.33
q55	.66	.44
q56	.56	.31

Examination of standardised residual values and MIs did not identify values worth noting and as such no further improvements to the model were undertaken.

Good construct reliability was observed for this model with a value of .82 indicating very good internal consistency. Convergent validity was low as indicated by an average variance extracted value of .26. Overall, the findings provide support for the Cultural Resilience factor. As presented in Figure 6, a final model for Cultural Resilience included thirteen items.

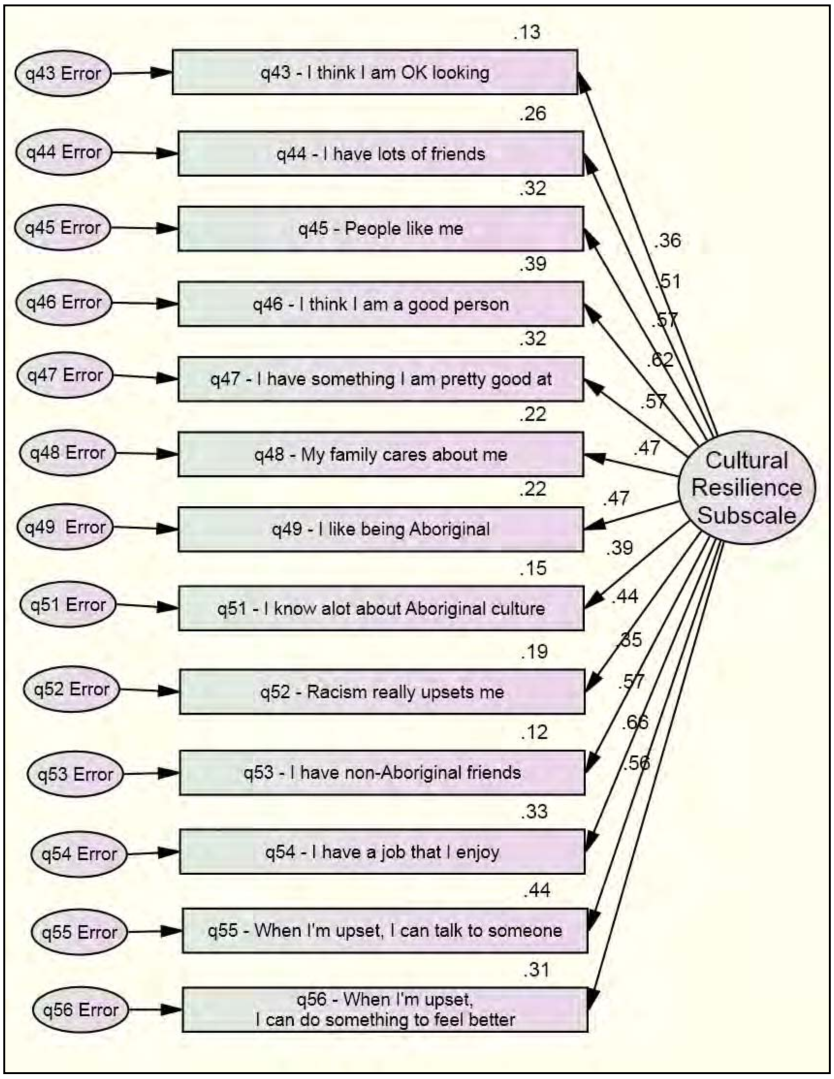

Figure 6: One factor model for Cultural Resilience Subscale

Discriminant Validity

Paswan (2009) defines discriminant validity as "*the extent to which a factor is truly distinct from other factors*". This can be demonstrated by comparing all average variance extracted (AVE) estimates of factors with their corresponding squared interfactor correlation (SIC) estimates. Where the AVE estimates are larger than the SIC estimates, the measured items have more in common with the factor they are associated with than they do with the other factors, and therefore demonstrate discriminant validity. Table 17 indicates that this is the case for the greater majority of factors that form the WASC-A. However there is one exception which is the relationship between the Depression and Anxiety factors. The high co-variance between Depression and Anxiety is not unexpected given the high co-occurrence of these disorders. Further research to investigate the relationship between Depression and Anxiety as measured by these subscales is warranted.

Table 17: Average Variance Extracted estimates versus Square Interfactor Correlation estimates for WASC-A subscale factors

1st Factor – 2nd Factor	1st Factor AVE	2nd Factor AVE	Interfactor Correlation	*** p-value <.001	Squared Interfactor Correlation (SIC)
Cultural Resilience – Depression	.26	.33	-.19	.005	.04
Cultural Resilience – Suicide	.26	.68	-.18	.004	.03
Cultural Resilience – Alcohol & Drug	.26	.89	-.06	***	.00
Cultural Resilience – Impulsivity	.26	.47	-.08	.261	.01
Cultural Resilience –Anxiety	.26	.38	-.04	.568	.00
Depression – Suicide	.33	.68	.54	***	.29
Depression – Alcohol & Drug	.33	.89	.37	***	.14
Depression – Impulsivity	.33	.47	.52	***	.27
Depression - Anxiety	.33	.38	.87	***	.76
Suicide – Alcohol & Drug	.68	.89	.59	***	.35
Suicide – Impulsivity	.68	.47	.48	***	.23
Suicide - Anxiety	.68	.38	.47	***	.23
Alcohol & Drug – Impulsivity	.89	.47	.15	.006	.02
Alcohol & Drug - Anxiety	.89	.38	.31	***	.09
Impulsivity - Anxiety	.47	.38	.50	***	.25

Concluding Remarks

These initial findings indicate that all subscales for the WASC-A possess at the least acceptable fit to the data, with the majority indicating very good fit. In other words, the sample data collected strongly supports the hypothesized factors (i.e. Depression, Suicide, Alcohol and Drug, Impulsivity, Anxiety, and Cultural Resilience) and their relative items. The subscales are further supported by other results regarding validity and reliability. For instance, convergent validity was satisfactory for the majority of the subscales indicating that items grouped together under a particular factor are indeed related to each other. In the instance where a subscale returned a low convergent validity, this did not impact model fit or internal consistency. Similarly, consistently high construct reliability for all subscales suggests that the individual items for each subscale produce similar results (i.e. they have internal consistency) and that the subscales typically represent the factors they purport to. In addition, the demonstration of discriminant validity for most WASC-A factors (with the exception of the Depression and Anxiety factors as noted previously) suggest that factors can be differentiated from each other, providing further support for the WASC-A and its utility.

Glossary of Terms

Average Variance Extracted (AVE) – A summary measure of convergence among a set of items representing a factor. It is the average percent of variation explained among the items. AVE estimates should be larger than the corresponding squared interfactor correlation (SIC) estimates indicating that the measured items have more in common with the factor they are associated with than with other factors.

Construct Reliability – Measure of reliability and internal consistency of the measured variables representing a latent factor.

Convergent Validity – Extent to which indicators of a specific factor converge or share a high proportion of variance in common. To assess this, factor loadings and average variance extracted (AVE) are examined.

Discriminant Validity – Extent to which a factor is truly distinct from other factors (i.e. unidimensional). This can be determined by comparing the Average Variance Extracted (AVE) estimates for each factor with the squared interfactor correlation (SIC) estimates associated with that factor.

Practical Significance – Assesses whether the result is useful (i.e. substantial enough to warrant action) in achieving the research objective.

Squared Interfactor Correlations (SIC) – The square root of the interfactor correlation between two factors. This estimate is used to determine discriminant validity.

Squared Multiple Correlations – Also referred to as the squared loadings and are used in calculating the Average Variance Extracted (AVE) for each factor.

Statistical Significance – Assesses whether the result is attributable to chance.

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