

An Exploratory Investigation of the Factor Structure of the Reynolds Intellectual Assessment Scales (RIAS)

Stefan C. Dombrowski
Rider University

Marley W. Watkins
Arizona State University

Michael J. Brogan
Rider University

This study investigated the factor structure of the Reynolds Intellectual Assessment Scales (RIAS) using rigorous exploratory factor analytic and factor extraction procedures. The results of this study indicate that the RIAS is a single factor test. Despite these results, higher order factor analysis using the Schmid–Leiman procedure indicates that all subtests are aligned with their theoretically consistent factors. All analyses in this study, including the minimum average partial test, parallel analysis, the Schmid–Leiman procedure, as well as principal factors with orthogonal and oblique rotation, support interpretation at the composite intelligence index level and suggest caution when moving to interpretation at the verbal and nonverbal index levels. The memory subtests should continue to be separated from the main IQ battery because of poor g-loadings and contribution to cross loadings of the intelligence subtests. Interpretation at the subtest level should be eschewed.

Keywords: *RIAS; exploratory factor analysis; Schmid–Leiman; intelligence testing; factor extraction decision-making*

The Reynolds Intellectual Assessment Scales (RIAS; Reynolds & Kamphaus, 2003) is an individually administered test of intelligence designed for individuals between the ages of 3 and 94. The RIAS has justifiably received laudatory commentary for its organized and expedient approach to the assessment of global intellectual functioning (Andrews, 2007; Dombrowski & Mrazik, 2008; Elliot, 2004). However, questions have been raised regarding the latent structure of the RIAS and whether more than one factor should be extracted (Bracken, 2005; Dombrowski & Mrazik, 2008).

From a theoretical or empirical perspective, the authors of the RIAS report that they were guided by Carroll's (1993) three stratum theory of cognitive ability and the work of Horn and Cattell (1966). However, exploratory factor analytic (EFA) procedures advocated

Authors' Note: Please address correspondence concerning this article to Stefan C. Dombrowski, PhD, Professor and Director, School Psychology Program, Rider University, 2083 Lawrenceville Road, Lawrenceville, NJ 08648; e-mail: sdombrowski@rider.edu.

by both Horn (1965; e.g., Horn's Parallel Analysis) and Carroll (1993; e.g., higher order factor analysis via the Schmid–Leiman procedure) were not undertaken by the test authors. Instead, when conducting exploratory analyses, the test authors relied solely on Principal Factors (PF) with varimax rotation to elucidate the structure of the RIAS. This is unfortunate because the derived factor structure of an IQ test via a factor analysis determines how the test should be interpreted by practitioners. The incorrect or inappropriate use of factor analysis and subsequent factor rotation can lead to specious interpretations and subsequent erroneous diagnostic decision making (DiStefano & Dombrowski, 2006).

There are two concerns with varimax rotation for use with intelligence tests. Gorsuch (1983) commented that “varimax is inappropriate if the theoretical expectation suggests a general factor may occur” (p. 185). Varimax rotation is also considered inappropriate when factors are highly correlated as in the case of tests of intelligence. Because of both concerns, an oblique rotation (e.g., promax) is necessary (Thompson, 2004). Although an oblique rotation is necessary, it is not singularly sufficient and an additional step is required. Gorsuch (1983) commented that higher order factors are implicit in all oblique rotations, so it is recommended that these factors be extracted and examined (Gorsuch, 1983).

One approach to examining and extracting higher order factors is through the Schmid–Leiman (1957) procedure. This procedure was advocated by Carroll (1993) and involves making first order factors orthogonal to second-order factors by first extracting the variance explained by the second-order factors. The next step in the procedure is to residualize the first-order factors of all the variance present in the second-order factors. Schmid–Leiman (1957) argued that this process “preserves the desired characteristics of the oblique solution” and “discloses the hierarchical structure of the variables” (p. 53). Carroll (1995) emphasized that orthogonal factors are appropriate only when produced in the context of a Schmid–Leiman solution: “I insist, however, that the orthogonal factors should be those produced by the Schmid–Leiman (1957) orthogonalization procedure” (Carroll, 1995, p. 437). Thus, from several perspectives, a case can be made that primary interpretative emphasis in understanding the latent structure of the RIAS should be placed on the EFA procedures of higher order factor analysis and PF with oblique (promax) rotation.

To determine the number of factors to extract, the professional manual reports that scree plots and eigenvalue levels were examined; however, scree plots were not provided, nor was standard information furnished regarding eigenvalue levels, extraction criteria (e.g., Kaiser > 1), percentage of variance accounted for by the factors, and communality statistics. This information would have enhanced capacity to critically evaluate the RIAS and whether interpretation might reasonably move beyond the higher order (*g*) factor to the level of the verbal, nonverbal, and composite memory indices. (For a well-written overview of how to interpret these data, please see Thompson, 2004). Even with the provision of this information, the inspection of scree plots and eigenvalue levels is considered a subjective and lenient approach to factor extraction that sometimes leads to overfactoring (Costello & Osborne, 2005; Frazier & Youngstrom, 2007). Consequently, two lesser known factor extraction procedures would have augmented factor extraction decision making: Horn's parallel analysis (HPA; Horn, 1966) and Velicer's Minimum Average Partial test (MAP; Velicer, 1976). Parallel analysis and MAP are statistically based and considered more accurate and rigorous procedures for determining the correct number of factors to

retain than are inspection of scree plots and eigenvalue levels (O'Connor, 2000; Velicer, Eaton, & Fava, 2000; Zwick & Velicer, 1986).

Parallel analysis (Horn, 1965) compares eigenvalues from the actual data to eigenvalues extracted from a correlation matrix of randomly generated, uncorrelated variables that contain the same dimensions as the original data set. If actual eigenvalues are greater than the eigenvalues from the random data set, then the factors are retained. Velicer's MAP test (Velicer, 1976) requests a number of principal component solutions, ranging from one solution to the number of variables included for analysis. At each step, the principal components are removed from the correlations and a matrix of partial correlations computed. The minimum average partial correlation across the solutions suggests the number of components to retain (O'Connor, 2000). Unfortunately, the RIAS Professional Manual did not include these two important factor extraction procedures. Because of this omission, and in consideration of the argument in favor of the two previously discussed EFA procedures, additional analyses of the RIAS normative sample are necessary.

This study was designed to furnish these additional analyses through evaluation of the RIAS using factor extraction and EFA procedures that were not utilized by the test authors but are considered appropriate based on the EFA literature (Fabrigar, Wegener, MacCallum, & Strahan, 1999). These analyses include PF with oblique (promax) rotation, higher order factor analysis using the Schmid-Leiman procedure, Horn's parallel analysis, and the Minimum Average Partial test. In addition, this study explored the factor structure of the RIAS using PF with orthogonal (varimax) rotation, the same procedure presented in the Professional Manual. Unlike the Professional Manual, which omitted key PF statistical information, this study's PF analysis furnished eigenvalue levels, communality statistics, and percentage of variance accounted for by factors. The combination of all analyses provided in this study should serve to enhance examiners' capacity to critically evaluate the factor structure of the RIAS and therefore make more informed judgments about clinical interpretation.

Method

Participants and Data

A total of 2,438 individuals aged 3 to 94 years were used in the standardization sample. The RIAS authors attempted to match the sample to the U.S. 2001 census on age, gender, educational attainment, and geographical location. Because it may be difficult to measure certain age groups (e.g., very young children), the test authors collected and reported information relative to five age groups: 3 to 5 years, 6 to 11 years, 12 to 18 years, 19 to 94 years, and the total sample (3 to 94 years). During the norming process, the five groups were examined independently.

Instrument

The RIAS is an individually administered measure of intellectual ability that yields a global Composite Intelligence index (CIX), a Verbal Intelligence index (VIX), and a Nonverbal Intelligence index (NIX). The verbal and nonverbal intelligence indices contain two subtests

each. The RIAS also includes a conormed, two-subtest memory composite that is separate from the global intelligence composite as well as a brief intelligence screening test called the Reynolds Intellectual Screening Test (RIST). The two verbal subtests include Guess What (GWH) and Verbal Reasoning (VRZ). The two nonverbal subtests include Odd-Item Out (OIO) and What's Missing (WHM). The two memory subtests include Verbal Memory (VRM) and Nonverbal Memory (NVM). Please see Dombrowski & Mrazik (2008) for a synopsis of subtest demands.

Analyses

The RIAS standardization sample was analyzed using several EFA methodologies. First, the intercorrelation matrices for the five age groups of the RIAS were analyzed using Bartlett's Test of Sphericity (Bartlett, 1954) and the Kaiser–Meyer–Olkin (KMO; Kaiser, 1974) statistic to ensure that the matrices were suitable for factor analysis. Second, scree plots and eigenvalue levels (> 1) were inspected to determine the number of factors to retain for rotation. Because of concerns about the leniency of these factor extraction approaches (Velicer & Jackson, 1990) and following EFA best practices advice (e.g., Thompson, 2004; Velicer, Eaton, & Fava, 2000), minimum average partials (MAP; Velicer, 1976) and parallel analysis (Horn, 1965) were also used to determine the number of factors to extract. These procedures were conducted using O'Conner's (2000) SPSS program. Next, and despite the results of factor extraction criteria suggesting a unidimensional model across all age groups, the intercorrelation matrices were subjected to principal axis analysis with varimax rotation for the four- and six-subtest configurations. The intercorrelation matrices were also subjected to a PF analysis with promax rotation ($k = 4$) because of the possibility of correlated factors (Gorsuch, 1983). Pattern coefficients of .32 or higher were determined to be salient (Tabachnick & Fidell, 2001). Finally, because the professional manual posits that the three-stratum theory of Carroll (1993) was influential in the creation of the RIAS, a higher order factor analysis using the Schmid–Leiman (1957) procedure was applied to the oblique first-order factors to elucidate the structure of the RIAS. Watkins' MacOrtho (2004) program was used to calculate the Schmid–Leiman solution.

Results

Results from Bartlett's Test of Sphericity (Bartlett, 1954) indicated that all correlation matrices (4- and 6- subtest configurations) across the five age ranges were not random. In addition, the Kaiser–Meyer–Olkin (KMO; Kaiser, 1974) statistic was at or above the minimum standard suggested by Kline (1994). Measures of sampling adequacy for each variable were also within reasonable limits. Thus, the correlation matrices were appropriate for factor analysis.

First-Order Factor Analysis

All factor extraction criteria (e.g., MAP, Horn's parallel analysis, inspection of scree plots and eigenvalues greater than 1.0) across the five age ranges suggested extracting only one factor for both the four- and six-subtest RIAS configurations (see Tables 1 & 2).

Table 1
Two Factor Principal Axis EFA With the RIAS Four-Subtest
Configuration Using Varimax and Promax Rotation

Subtest	Unrotated Factor	Varimax Structure Coefficients		Promax Pattern Coefficients		Promax Structure Coefficients		h ²
		I	II	I	II	I	II	
Total sample (<i>n</i> = 2,438)								
GWH	.83	.73	.42	.78	.08	.84	.70	.71
VRZ	.81	.73	.40	.80	.04	.83	.67	.69
OIO	.69	.37	.62	.12	.62	.61	.72	.52
WHM	.63	.31	.59	.05	.63	.55	.67	.45
Eigenvalues		2.59	.61					
% Variance		55.0%	4.0%					
Corr. Factor I & II				<i>r</i> = .79				
3 to 5 (<i>n</i> = 395)								
GWH	.71	.66	.34	.72	.02	.74	.59	.55
VRZ	.77	.69	.40	.73	.09	.79	.65	.63
OIO	.70	.37	.63	.10	.65	.61	.73	.53
WHM	.62	.30	.59	.03	.64	.52	.66	.43
Eigenvalues		2.43	.66					
% Variance		49.5%	4.3%					
Corr. Factor I & II				<i>r</i> = .78				
6 to 11 (<i>n</i> = 611)								
GWH	.78	.72	.34	.78	.02	.80	.60	.64
VRZ	.79	.73	.35	.79	.03	.81	.61	.66
OIO	.61	.32	.57	.10	.58	.53	.65	.43
WHM	.51	.23	.54	-.01	.59	.43	.58	.34
Eigenvalues		2.31	.74					
% Variance		46.5%	5.2%					
Corr. Factor I & II				<i>r</i> = .74				
12 to 18 (<i>n</i> = 402)								
GWH	.88	.79	.43	.83	.08	.90	.72	.80
VRZ	.85	.78	.38	.86	.01	.87	.67	.76
OIO	.60	.30	.58	.05	.62	.52	.65	.43
WHM	.64	.32	.63	.07	.63	.55	.69	.47
Eigenvalues		2.60	.64					
% Variance		56.4%	5.2%					
Corr. Factor I & II				<i>r</i> = .76				
19 to 94 (<i>n</i> = 1,030)								
GWH	.87	.71	.50	.71	.20	.87	.77	.76
VRZ	.83	.76	.40	.85	.00	.85	.69	.73
OIO	.75	.46	.61	.23	.57	.69	.75	.58
WHM	.70	.34	.66	.02	.73	.61	.74	.55
Eigenvalues		2.82	.52					
% Variance		62.1%	3.6%					
Corr. Factor I & II				<i>r</i> = .81				

Note: GWH = Guess What; VRZ = Verbal Reasoning; OIO = Odd Item Out; WHM = What's Missing. Salient factor structure coefficients (>.44) based on Comrey and Lee's (1992) classifications are presented in bold.

Four-subtest configuration (PF with varimax and promax rotation). Despite factor extraction criteria suggesting extraction of only one factor, two factors were extracted in accord with the proposed factor structure indicated in the Professional Manual. Across all age ranges, PF with varimax (orthogonal) rotation of a two-factor solution indicated that all subtests were associated with their theoretically proposed factors (Table 1). All verbal subtests produced good g-loadings (.70 or higher) across all five age groups. The nonverbal subtests produced fair g-loadings (.50 to .69) in the school aged ranges (6 to 18) and good g-loadings in the 19 to 94 age range. When investigating the subtests in relation to their respective factors, the loadings of the verbal subtests on the verbal factor were in the good range across all age groups except the 3 to 5 age group where the loading was considered fair (.66 and .69 for GWH and VRZ, respectively). The nonverbal subtests loaded in the fair range with the nonverbal factor across all age ranges.

Despite theoretically consistent alignment of subtests with respective factors, eigenvalue levels across all five age ranges indicated a unidimensional model (Table 1). The first factor accounted for 46.5% (age 6 to 11) to 62.1% (age 19 to 94) of the variance. The second factor accounted for 3.6% to 5.2% of the variance depending on the age range analyzed.

PF with promax (oblique) rotation of the forced two-factor solution produced salient factor pattern coefficients with each subtest aligning with its theoretically consistent factor (Table 1). The pattern of verbal and nonverbal subtest alignment with their respective factors was similar to that with varimax rotation. The verbal subtests had factor pattern coefficients in the good range, whereas the nonverbal subtests produced factor pattern coefficients in the fair range. Promax rotation indicated that Factors I and II were highly correlated, ranging from $r = .74$ for the 6 to 11 age range to $.81$ for the 19 to 94 age range. Because of highly correlated factors, promax rotation of the four-subtest configuration suggested a lack of divergent validity and the need for higher order factor analysis.

Six-subtest configuration (PF with varimax and promax rotation). Both two and three factors were extracted in accord with the proposed factor structure presented in the Professional Manual. The three-factor, six-subtest configuration did not produce a clear third factor so the results of this analysis was not furnished.

Across all age ranges, varimax rotation of the two-factor, six-subtest configuration indicated that all subtests were aligned with their theoretically proposed factors (Table 2). However, there was a considerable degree of cross loading with the opposite factor (e.g., VRZ and OIO at 3 to 5; GWH at 12 to 18; GWH and OIO at 19 to 94). In addition, a six-subtest configuration tended to produce poor g-loadings ($< .50$) for the memory subtests in the school age ranges (e.g., 3 to 18) and even produced a poor g-loading (.49) for WHM at the 6 to 11 age range. Table 2 describes the proportion of variance accounted for by each factor. The first factor accounted for 39.1% (age 6 to 11) to 53.9% (age 19 to 94) of the variance. The second factor accounted for 3.8% to 5.3% of the variance depending on the age range analyzed.

Promax (oblique) rotation of the forced two-factor, six-subtest configuration produced salient factor pattern coefficients that were aligned with their theoretically proposed factors (Table 2). Promax rotation revealed that Factors I and II were highly correlated, ranging from $r = .74$ for the 12 to 18 age range to $.79$ for the 19 to 94 age range. Promax rotation

Table 2
Two Factor Principal Axis EFA With the RIAS Six-Subtest
Configuration Using Varimax and Promax Rotation

Subtest	Unroated Factor	Varimax structure coefficients		Promax pattern coefficients		Promax structure coefficients		h ²
		I	II	I	II	I	II	
Total Sample (<i>n</i> = 2,348)								
GHW	.80	.71	.41	.74	.10	.82	.67	.67
VRZ	.82	.78	.36	.87	-.01	.86	.65	.74
VRM	.53	.47	.27	.49	.06	.54	.44	.30
OIO	.72	.37	.67	.08	.69	.61	.76	.58
WHM	.62	.35	.53	.15	.51	.55	.63	.41
NVM	.57	.25	.57	-.01	.63	.47	.62	.38
Eigenvalues		2.81	.26					
% Variance		46.8%	4.3%					
Corr. Factor I & II				<i>r</i> = .77				
3 to 5 (<i>n</i> = 395)								
GHW	.70	.64	.32	.67	.06	.72	.56	.52
VRZ	.78	.76	.32	.84	-.02	.82	.60	.68
VRM	.56	.54	.24	.58	.00	.59	.44	.34
OIO	.73	.38	.68	.10	.70	.62	.78	.61
WHM	.60	.36	.50	.19	.47	.53	.61	.38
NVM	.47	.17	.52	-.09	.61	.37	.55	.30
Eigenvalues		2.53	.30					
% Variance		42.1%	4.9%					
Corr. Factor I & II				<i>r</i> = .74				
6 to 11 (<i>n</i> = 611)								
GHW	.77	.71	.36	.75	.05	.79	.61	.63
VRZ	.79	.72	.39	.75	.08	.81	.64	.67
VRM	.48	.50	.17	.58	-.08	.52	.35	.28
OIO	.64	.30	.63	.04	.66	.53	.69	.48
WHM	.49	.22	.50	.00	.54	.40	.54	.30
NVM	.50	.21	.52	-.03	.57	.40	.56	.31
Eigenvalues		2.35	.31					
% Variance		39.1%	5.1%					
Corr. Factor I & II				<i>r</i> = .74				
12 to 18 (<i>n</i> = 402)								
GHW	.85	.76	.42	.78	.11	.86	.68	.75
VRZ	.87	.84	.35	.92	-.02	.91	.65	.83
VRM	.42	.41	.17	.45	-.01	.44	.31	.19
OIO	.65	.25	.70	-.05	.78	.52	.75	.56
WHM	.62	.38	.50	.23	.44	.55	.61	.40
NVM	.53	.25	.52	.05	.53	.44	.57	.33
Eigenvalues		2.72	.33					
% Variance		45.4%	5.5%					
Corr. Factor I & II				<i>r</i> = .72				

(continued)

Table 2 (continued)

Subtest	Unrotated Factor	Varimax structure coefficients		Promax pattern coefficients		Promax structure coefficients		h ²
		I	II	I	II	I	II	
19 to 94 (<i>n</i> = 1,030)								
GHW	.84	.70	.49	.68	.20	.84	.74	.73
VRZ	.83	.81	.36	.92	-.05	.88	.68	.78
VRM	.60	.49	.35	.47	.15	.60	.53	.37
OIO	.77	.44	.66	.18	.64	.68	.78	.62
WHM	.69	.38	.61	.13	.61	.61	.71	.51
NVM	.63	.29	.61	.01	.69	.53	.68	.46
Eigenvalues		3.23	.23					
% Variance		53.9%	3.8%					
Corr. Factor I & II				<i>r</i> = .79				

Note: GHW = Guess What; VRZ = Verbal Reasoning; OIO = Odd Item Out; WHM = What's Missing VRM = Verbal Memory; NVM = Nonverbal Memory. Salient factor structure coefficients (>.44) based on Comrey and Lee's (1992) classifications are presented in bold.

of six-subtest configuration suggested a lack of divergent validity and the need for higher order factor analysis.

Higher Order Factor Analysis

Four-subtest configuration. Schmid–Leiman results for the four-subtest configuration are presented in Table 3. Results from this analysis suggest that the higher order factor, across all age ranges analyzed, accounted for the greatest portion of the total variance, common variance, and subtest variance. Depending on the age range analyzed, the higher order (*g*) factor accounted for 12% (WHM; age 12 to 18) to 54% (GHW; age 19 to 95) of the respective RIAS subtest variance. The higher order factor also accounted for the largest portion of total variance (28.6% for ages 6 to 11 to 45.1% for ages 19 to 95) and common variance (56.3% for ages 6 to 11 to 71.0% for ages 19 to 95). The verbal factor accounted for 10.2% (age 3 to 5) to 15.1% (age 12 to 18) of the total variance and 17.2% (age 19 to 95) to 28.2% (age 6 to 11) of the common variance beyond the general factor. The nonverbal factor accounted for 7.5% (age 19 to 95) to 8.2% (age 12 to 18) of the total variance and 11.8% (age 19 to 95) to 15.6% (age 3 to 5) of common variance beyond the general factor. Higher order factor analysis generally produced fair *g*-loadings for subtests across all age ranges with the exception of OIO (.43) at ages 6 to 8 and WHM (.35) at ages 12 to 18 which were in the poor range.

All subtests were associated with their theoretically consistent factors. The verbal subtests produced fair to poor factor loadings with the verbal factor, whereas the nonverbal subtests produced poor factor loadings on the nonverbal factor across all age ranges.

Six-subtest configuration. Schmid–Leiman results for the six-subtest, two-factor configuration are presented in Table 4. Depending on the age range analyzed, the higher order (*g*) factor accounted for 24.3% to 37.5% of the RIAS subtest variance, the greatest portion

Table 3
Sources of Variance on the RIAS Normative Sample According
to an Orthogonal Higher Order Factor Model
With Schmid-Leiman Solution (Four-Subtest Configuration)

Subtest	General		Verbal		Nonverbal		h ²	u ²
	<i>b</i>	Var	<i>b</i>	Var	<i>B</i>	Var		
Total Sample (<i>n</i> = 2,438)								
GWH	.68	.46	.48	.23	.05	.00	.69	.31
VRZ	.66	.44	.49	.24	.03	.00	.68	.32
OIO	.59	.34	.07	.01	.38	.15	.49	.51
WHM	.54	.29	.03	.00	.39	.15	.44	.56
% Total Var		38.3%		11.7%		7.4%	57.5%	42.5%
% Common Var		66.6%		20.4%		12.9%		
3 to 5 (<i>n</i> = 395)								
GWH	.58	.34	.45	.20	.01	.00	.54	.46
VRZ	.63	.40	.45	.20	.05	.00	.61	.39
OIO	.59	.35	.06	.00	.41	.17	.52	.48
WHM	.52	.27	.02	.00	.40	.16	.43	.57
% Total Var		33.9%		10.2%		8.2%	52.3%	47.7%
% Common Var		64.8%		19.5%		15.6%		
6 to 11 (<i>n</i> = 611)								
GWH	.60	.36	.54	.29	.02	.00	.65	.35
VRZ	.59	.35	.53	.28	.01	.00	.63	.37
OIO	.43	.18	.00	.00	.40	.16	.34	.66
WHM	.50	.25	.07	.00	.39	.16	.59	.59
% Total Var		28.6%		14.3%		7.8%	50.7%	49.3%
% Common Var		56.3%		28.2%		15.5%		
12 to 18 (<i>n</i> = 402)								
GWH	.70	.48	.54	.29	.05	.00	.78	.22
VRZ	.67	.44	.56	.31	.01	.00	.78	.25
OIO	.51	.26	.03	.00	.40	.16	.42	.58
WHM	.35	.12	.05	.00	.41	.17	.29	.71
% Total Var		32.7%		15.1%		8.2%	56.1%	43.9%
% Common Var		58.4%		27.0%		14.7%		
19 to 94 (<i>n</i> = 1,030)								
GWH	.73	.54	.41	.17	.11	.01	.72	.28
VRZ	.69	.48	.50	.25	.00	.00	.73	.27
OIO	.65	.42	.13	.02	.33	.11	.54	.46
WHM	.61	.37	.01	.00	.42	.18	.55	.45
% Total Var		45.1%		10.9%		7.5%	63.5%	36.5%
% Common Var		71.0%		17.2%		11.8%		

Note: GWH = Guess What; VRZ = Verbal Reasoning; OIO = Odd Item Out; WHM = What's Missing. *b*= loading of subtest on factor (factor structure coefficient); Var= percent variance explained in the subtest; h²= communality; u²= uniqueness.

Table 4
Sources of Variance on the RIAS Normative Sample
According to an Orthogonal Higher Order Factor Model
with Schmid-Leiman Solution (Six-Subtest Configuration)

Subtest	General		Verbal		Nonverbal		h ²	u ²
	b	Var	b	Var	B	Var		
Total Sample								
GWH	.64	.41	.48	.23	.07	.00	.64	.36
VRZ	.66	.43	.56	.31	-.01	.00	.74	.26
OIO	.59	.35	.05	.00	.45	.20	.56	.44
WHM	.51	.26	.10	.01	.33	.11	.38	.62
VRM	.43	.18	.32	.10	.04	.00	.28	.00
NVM	.47	.22	-.01	.00	.40	.16	.39	.00
% Total Var		31.0%		10.9%		8.0%	49.8%	28.0%
% Common Var		62.2%		21.8%		16.0%		
3 to 5								
GWH	.54	.29	.45	.21	.04	.00	.50	.50
VRZ	.61	.37	.56	.32	-.02	.00	.68	.32
OIO	.59	.35	.07	.00	.47	.22	.58	.42
WHM	.49	.24	.13	.02	.31	.10	.35	.65
VRM	.43	.19	.39	.15	.00	.00	.34	.00
NVM	.39	.15	-.06	.00	.41	.17	.32	.00
% Total Var		26.4%		11.7%		8.1%	46.2%	31.5%
% Common Var		57.2%		25.2%		17.6%		
6 to 11								
GWH	.60	.35	.51	.26	.04	.00	.61	.39
VRZ	.62	.38	.51	.26	.06	.00	.64	.36
OIO	.52	.27	.03	.00	.45	.20	.47	.53
WHM	.40	.16	.00	.00	.37	.13	.29	.71
VRM	.37	.14	.39	.15	-.05	.00	.29	.00
NVM	.41	.16	-.02	.00	.39	.15	.31	.00
% Total Var		24.3%		11.2%		8.2%	43.7%	33.1%
% Common Var		55.6%		25.6%		18.8%		
12 to 18								
GWH	.65	.42	.54	.29	.08	.01	.71	.29
VRZ	.65	.43	.64	.41	-.01	.00	.83	.17
OIO	.53	.28	-.04	.00	.54	.29	.58	.42
WHM	.49	.24	.16	.03	.31	.09	.36	.64
VRM	.32	.10	.31	.10	-.01	.00	.20	.00
NVM	.42	.18	.04	.00	.37	.14	.32	.00
% Total Var		27.4%		13.7%		8.8%	49.8%	25.4%
% Common Var		54.9%		27.4%		17.7%		
19 to 94								
GWH	.70	.49	.42	.17	.13	.02	.68	.32
VRZ	.69	.47	.57	.32	-.03	.00	.80	.20
OIO	.65	.42	.11	.01	.39	.16	.58	.42
WHM	.58	.34	.08	.01	.37	.14	.49	.51

(continued)

Table 4 (continued)

Subtest	General		Verbal		Nonverbal		h ²	u ²
	b	Var	b	Var	B	Var		
VRM	.50	.25	.29	.08	.09	.01	.34	.00
NVM	.53	.28	-.01	.00	.42	.18	.46	.00
% Total Var		37.5%		10.0%		8.3%	55.8%	24.2%
% Common Var		67.3%		17.9%		14.8%		

Note: GWH = Guess What; VRZ = Verbal Reasoning; OIO = Odd Item Out; WHM = What's Missing VRM = Verbal Memory; NVM = Nonverbal Memory. b= loading of subtest on factor (factor structure coefficient); Var= percent variance explained in the subtest; h²= communality; u²= uniqueness.

of the total variance, and greatest portion of common variance. The verbal factor accounted for 10.0% to 13.7% of the total variance and 17.9% to 27.4% of common variance beyond the general factor. The nonverbal factor accounted for 8.0% to 8.8% of the total variance and 14.8% to 18.8% of common variance beyond the general factor.

Higher order factor analysis of a six-subtest, two-factor configuration produced fair *g*-loadings (.50 to .69) for the verbal subtests and fair to poor (<.50) *g*-loadings for the nonverbal subtests. The memory subtests both loaded on the general factor in the poor range across all age ranges. With respect to the two subordinate factors, all subtests were aligned with their theoretically proposed factors. The verbal IQ subtests loaded with the verbal factor in the fair to poor range, whereas the nonverbal subtests loaded in the poor range on the nonverbal factor. Both verbal and nonverbal memory subtests loaded in the poor range with the respective verbal and nonverbal factors. Results for the Schmid–Leiman analysis are not reported for the three-factor extraction because of a lack of support for this configuration.

Discussion

Because of limited EFA technical information in the Professional Manual and the need for additional EFA analyses (e.g., higher order factor analysis using Schmid–Leiman procedure; Velicer's MAP; Horn's PA) that are considered more appropriate, this study was undertaken to explore the factor structure and the latent constructs of the RIAS. The RIAS Professional Manual, although clearly written, did not include commonly furnished EFA statistical information for its PF analyses including scree plots, eigenvalue levels, percentage of variance accounted for by each factor, and detailed EFA factor extraction decision-making criteria. This information is critical for determining the number of factors to retain (Thompson, 2004).

In addition to inspection of scree plots and eigenvalue levels to determine the number of factors to retain for rotation, this study used two approaches that have been deemed factor extraction best practices—PA and MAP. The results of all four factor extraction procedures converged to suggest that the RIAS is a single factor test. This conclusion is consistent with theoretical considerations from the EFA literature, which requires a minimum of three variables (i.e., subtests) per factor to locate a discrete factor (Costello & Osborne, 2005; Fabrigar et al., 1999). Based on this literature and the factor extraction analyses conducted in this study, extraction of more than one factor of the RIAS may be problematic.

Despite converging empirical and theoretical evidence that the RIAS is a single factor test, this study analyzed the correlation matrices in accord with the posited factor structure presented in the Professional Manual. Because the Professional Manual did not furnish detailed statistical information on its PF analysis, this study undertook a principal factors analysis not only with varimax (orthogonal) but also with promax (oblique) rotation. Both rotations were included to replicate and then supplement the analyses provided in the Professional Manual. The results of these analyses across all age ranges of the two-factor, four-subtest configurations provided evidence for the general factor. In addition, all subtests were associated with their theoretically consistent factors. However, the *g*-factor accounted for the largest proportion of variance. Promax rotation indicated that the two RIAS factors are highly correlated ($r = .74-.81$) across the five age ranges, again providing evidence for a unidimensional model.

The two-subtest, six-factor configuration across all PF analyses tended to produce poor *g* loadings on some subtests (e.g., memory subtests) and cross loadings on others. As a result, this configuration was determined to be less viable than a four-subtest, two-factor configuration wherein the memory subtests should be considered separate from the IQ portion of the RIAS. Promax rotation demonstrated that the two RIAS factors are highly correlated ($r = .72-.79$) across the five age ranges, providing further evidence that the RIAS is a single factor test. Promax rotation suggested a lack of divergent validity and a need for a higher order factor analysis.

A higher order factor analysis using the Schmid–Leiman procedure—the approach recommended by Carroll (1993) when investigating tests of intelligence particularly those that are predicated on his theory—indicated that respective subtests are aligned with their theoretically posited factors. However, the general factor accounted for the largest proportion of total and common variance, lending itself to a unidimensional model. Across all analyses, the three factor solution was deemed untenable and the results were not reported as a result.

Conclusion and Implication for Practitioners

A higher order factor analysis using a Schmid–Leiman solution of the RIAS correlation matrices provided evidence for the four-subtest, two-factor model presented in the Professional Manual. However, the total and common variance accounted for by the general factor exceeded that of the first order verbal and nonverbal factors suggesting extreme caution when moving to interpretation beyond the general factor. A PF with oblique (promax) rotation indicated that the first and second factors were very highly correlated, supporting a unidimensional model. All factor analytic techniques suggested poor *g*-loadings when a six-subtest configuration was used, particularly those of the memory subtests. Both PF analyses and higher order factor analyses indicate that the memory subtests should be separated from the main IQ battery. All analyses also provided evidence that the RIAS is best interpreted at the *g*-factor (CIX).

The factor extraction techniques of PA and MAP along with the more lenient factor extraction techniques of inspection of scree plots and eigenvalue levels indicated extraction of only one factor. Theoretical considerations from the EFA literature also posit that the RIAS should be regarded as a single factor test because a minimum of three subtests per factor is necessary to move beyond a unidimensional model (Costello & Osborne, 2005). Thus, from both a

theoretical and empirical perspective, the RIAS appears to be a single factor test. This is not singular criticism of the RIAS but rather most available IQ tests ([Distefano & Dombrowski, 2006](#); [Frazier & Youngstrom, 2007](#); [Watkins, Wilson, Kotz, Carbone, & Babula, 2006](#)).

The results of our study have several practical implications for the interpretation of the RIAS. First, the RIAS is most appropriately interpreted at the Composite Intelligence index (CIX) level. Although PF with varimax rotation and higher order factor analysis via a Schmid–Leiman solution suggest a tendency toward the posited first (verbal & nonverbal) and second (composite IQ) order factors, the preponderance of analyses in this study indicate that interpretation of the composite IQ index should not be overlooked in favor of interpretation at the verbal and nonverbal index level. Practitioners seeking to make verbal–nonverbal distinctions should consider the administration of additional instruments that specifically target these cognitive ability areas. Practitioners should also eschew interpretation at the level of the subtest. In addition, the RIAS Professional Manual incorporates supplemental normative tables providing for inclusion of the memory subtests in the composite IQ index. This table should not be referenced because of the poor *g*-loadings of the memory subtests and their contribution to the dilution of *g*-loadings and cross loadings of the other subtests. Thus, the memory subtests should continue to be separated from the main test battery. And, additional validity studies are necessary to determine the memory composite’s relationship with the construct of memory. In totality, the RIAS is a solid measure of psychometric *g* and provides an expedient approach to the measurement of overall cognitive ability. Caution should be exercised when moving beyond that level of interpretation.

References

- Andrews, J. J. W. (2007). RIAS: Reynolds Intellectual Assessment Scales. *Journal of Psychoeducational Assessment, 25*, 402–408.
- Bartlett, M. S. (1954). A further note on the multiplying factors for various X² approximations in factor analysis. *Journal of the Royal Statistical Society, 16*, 296–298.
- Bracken, B. A. (2005). Reynolds Intellectual Assessment Scales and the Reynolds Intellectual Screening Test. In R. A. Spies & B. S. Plake (Eds.), *The sixteenth mental measurements yearbook* (pp. 892–894). Lincoln, NE: Buros Institute of Mental Measurements.
- Comrey, A. L., & Lee, H. B. (1992). *A first course in factor analysis*, 2nd ed. Hillsdale, NJ: Erlbaum.
- Carroll, J. B. (1993). *Human cognitive abilities: A survey of factor analytic studies*. New York: Cambridge University Press.
- Carroll, J. B. (1995). On methodology in the study of cognitive abilities. *Multivariate Behavioral Research, 30*, 429–452.
- Costello, A. B., & Osborne, J. W. (2005). Best practices in exploratory factor analysis: Four recommendations for getting the most from your analysis. *Practical Assessment, Research & Evaluation, 10*, 1–9.
- DiStefano, C., & Dombrowski, S. C. (2006). Investigating the theoretical structure of the Stanford-Binet, Fifth Edition. *Journal of Psychoeducational Assessment, 24*, 123–136.
- Dombrowski, S. C., & Mrazik, M. (2008). Test review: Reynolds Intellectual Assessment Scales. *Canadian Journal of School Psychology, 23*, 223–230.
- Elliot, R. W. (2004). Test review: Reynolds Intellectual Assessment Scales. *Archives of Clinical Neuropsychology, 19*, 325–328.
- Fabrigar, L. R., Wegener, D. T., MacCallum, R. C., & Strahan, E. J. (1999). Evaluating the use of exploratory factor analysis in psychological research. *Psychological Methods, 4*, 272–299.

- Frazier, T. W., & Youngstrom, E. A. (2007). Historical increase in the number of factors measured by commercial tests of cognitive ability: Are we overfactoring? *Intelligence, 35*, 169-182.
- Gorsuch, R. L. (1983). *Factor analysis*. Hillsdale, NJ: Lawrence Erlbaum.
- Horn, J. (1966). A rationale and test for the number of factors in factor analysis. *Psychometrika, 30*, 179-185.
- Horn, J. L., & Cattell, R. B. (1966). Refinement and test of the theory of fluid and crystallized general intelligences. *Journal of Educational Psychology, 57*, 253-270.
- Kaiser, H. F. (1974). An index of factorial simplicity. *Psychometrika, 39*, 31-36.
- Kline, P. (1994). *An easy guide to factor analysis*. NY: Routledge.
- O'Connor, B. P. (2000). SPSS and SAS programs for determining the number of components using parallel analysis and Velicer's MAP test. *Behavior Research Methods, Instruments, & Computers, 32*, 396-402.
- Reynolds, C. R., & Kamphaus, R. W. (2003). *Reynolds Intellectual Assessment Scales: Professional manual*. Lutz, FL: PAR.
- Schmid, J., & Leiman, J. M. (1957). The development of hierarchical factor solutions. *Psychometrika, 22*, 53-61.
- Tabachnick, B. G., & Fidell, L. S. (2001). *Using Multivariate Statistics*. Boston: Allyn & Bacon.
- Thompson, B. (2004). *Exploratory and confirmatory factor analysis: Understanding concepts and application*. Washington, DC: American Psychological Association.
- Velicer, W. F. (1976). Determining the number of components from the matrix of partial correlations. *Psychometrika, 41*, 321-327.
- Velicer, W. F., Eaton, C. A., & Fava, J. L. (2000). Construct explication through factor or component analysis: A review and evaluation of alternative procedures for determining the number of factors or components. In R. D. Goffin & E. Helms (Eds.), *Problems and solutions in human assessment: Honoring Douglas N. Jackson at seventy* (pp. 41-71). Norwell, MA: Springer.
- Velicer, W. F., & Jackson, D. N. (1990). Component analysis versus common factor analysis—Some further observations. *Multivariate Behavioral Research, 25*, 97-114.
- Watkins, M. W. (2004). MacOrtho [Computer Software]. State College, PA: Author.
- Watkins, M. W., Wilson, S. M., Kotz, K. M., Carbone, M. C., & Babula, T. (2006). Factor structure of the Wechsler Intelligence Scale for Children-Fourth Edition among referred students. *Educational and Psychological Measurement, 66*, 975-983.
- Zwick, W. R., & Velicer, W. F. (1986). Comparison of five rules for determining the number of components to retain. *Psychological Bulletin, 99*, 432-442.