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Higher-order exploratory factor analysis of the Reynolds Intellectual Assessment Scales with a referred sample

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Abstract

The factor structure of the Reynolds Intellectual Assessment Scales (RIAS; [Reynolds, C.R., & Kamphaus, R.W. (2003). *Reynolds Intellectual Assessment Scales.* Lutz, FL: Psychological Assessment Resources, Inc.]) was investigated with a large (N=1163) independent sample of referred students (ages 6–18). More rigorous factor extraction criteria (viz., Horn's parallel analysis (HPA); [Horn, J.L. (1965). A rationale and test for the number of factors in factor analysis. *Psychometrika*, 30, 179–185.], and Minimum Average Partial (MAP) analysis; [Velicer, W.F. (1976). Determining the number of components from the matrix of partial correlations. *Psychometrika*, 41, 321–327.]), in addition to those used in RIAS development, were investigated. Exploratory factor analyses using both orthogonal and oblique rotations and higher-order exploratory factor analyses using the Schmid and Leiman [Schmid, J., and Leiman, J.M. (1957). The development of hierarchical factor solutions. *Psychometrika*, 22, 53–61.] procedure were conducted. All factor extraction criteria indicated extraction of only one factor. Oblique rotations resulted in different results than orthogonal rotations, and higher-order factor analysis indicated the largest amount of

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variance was accounted for by the general intelligence factor. The proposed three-factor solution was not supported. Implications for the use of the RIAS with similarly referred students are discussed.

Keywords: Intellectual assessment; Intelligence; Exploratory factor analysis; Higher-order; Schmid–Leiman; Reynolds Intellectual Assessment Scales (RIAS)

Current views on intelligence tests are far from unanimous. Perhaps more than any other debate within the school psychology and special education communities, that over the manner in which students with learning disabilities (LD) should be identified illuminates the broad spectrum of views on the need for intelligence testing. Some argue that the construct of intelligence is a necessary component in the definition of LD and, consequently, should be evaluated to determine whether students should be classified as LD (e.g., Kavale & Forness, 2000; Naglieri, 2005; Schrank et al., 2004; Scruggs & Mastropieri, 2002). Others contend that intelligence testing should not be a predominant component of LD identification and that a response to intervention (RTI) approach is the most valid way to determine LD (e.g., Fletcher, Coulter, Reschly, & Vaughn, 2004; Gresham, 2001; Gresham et al., 2005). Those taking an RTI perspective argue that school psychologists spend far too much time administering intelligence tests and far too little time providing direct intervention and consultation services to students, parents, and teachers. Interestingly, however, some RTI advocates concede a place for intelligence tests in the identification of LD, stating that intelligence tests would be useful in ruling out mental retardation as a possible cause of learning difficulties (e.g., Gresham et al., 2005). According to these advocates, a brief or screening measure of intelligence would be sufficient for making diagnostic decisions.

Research on profile analysis of comprehensive intelligence tests points to the potential sufficiency of abbreviated measures for estimating general intelligence. A possible benefit of using comprehensive intelligence tests instead of briefer measures is their prospective ability to produce unique subtest profile patterns for different populations of students, which could potentially inform treatment approaches. A large body of literature has accumulated indicating that profile analysis is unreliable, unique profile patterns are not reliably characteristic of special populations of students, and profile patterns lack long-term stability (Canivez & Watkins, 1998, 2001; Glutting, McDermott, Konold, Snelbaker, & Watkins, 1998; Glutting, McDermott, Watkins, Kush, & Konold, 1997; Macmann & Barnett, 1997; McDermott, Fantuzzo, Glutting, Watkins, & Baggaley, 1992; Watkins & Canivez, 2004). Therefore, for the purposes of estimating an individual's general intellectual functioning without concern for profile analysis, instruments that consist of fewer subtests than traditional intelligence tests might be similarly effective but much more time- and cost-efficient.

The Reynolds Intellectual Assessment Scales (RIAS; Reynolds & Kamphaus, 2003) was designed, in part, to provide psychologists a quicker assessment of intelligence than that derived from traditional intelligence tests. Consequently, the average administration time of the RIAS is 20 to 25 min for the core battery and 30 to 35 min when the two supplemental memory subtests are also administered (Reynolds & Kamphaus). The average RIAS administration time is approximately half that of the Wechsler Intelligence Scale for Children-Fourth Edition (WISC-IV; Wechsler, 2003), which has an average administration time of 65 to 80 min. Elliott (2004) stated, "the RIAS will become a very popular measure of intelligence for school districts that are under serious pressure to provide measures of intelligence for determination of special education and program needs, but to do so at a lower cost and in a more rapid fashion" (p. 325).

Although Reynolds and Kamphaus (2003) referred to the RIAS as a "comprehensive measure of verbal and nonverbal intelligence and of general intelligence" (p. 12), it includes only four core subtests. Two additional subtests purportedly measure verbal and nonverbal memory and reportedly load onto a separate memory factor, labeled the Composite Memory Index (CMX). Reynolds and Kamphaus argued that the RIAS is not an abbreviated or short form assessment of intelligence; however, other intellectual assessment measures consisting of similar numbers of subtests (e.g., Wechsler Abbreviated Scale of Intelligence [The Psychological Corporation, 1999] and Kaufman Brief Intelligence Test [Kaufman & Kaufman, 1990]) are characterized as brief or abbreviated measures.

According to Reynolds and Kamphaus (2003), one of their major goals was to develop a psychometrically sound measure of general intelligence (*g*) and its major components: verbal and nonverbal intelligence. They suggested that the RIAS is closely aligned with the Cattell–Horn model of intelligence (Horn & Cattell, 1966) in that the subtests of the Verbal (VIX) and Nonverbal Intelligence Indexes (NIX) were designed to be accordant with its constructs of crystallized and fluid intelligence. Furthermore, Reynolds and Kamphaus stated that the development of the RIAS was influenced by Carroll's (1993) three-stratum theory, with the Composite Intelligence Index (CIX) purportedly serving as an indicator of stratum three (i.e., *g*) and the VIX and NIX purportedly serving as indicators of stratum two.

Two exploratory factor analyses (EFA) of the standardization data were conducted to examine the internal structure of the RIAS, with one examining the four intelligence subtests and the other examining these subtests combined with the two memory subtests (Reynolds & Kamphaus, 2003). To determine the number of factors to retain, Reynolds and Kamphaus incorporated Cattell's scree test and the Kaiser criterion (i.e., eigenvalues greater than one). Once the factors were extracted, they were rotated using Varimax (orthogonal) rotation. Additionally, Reynolds and Kamphaus used confirmatory factor analyses (CFA) to test the fit of the one-, two-, and three-factor models.

Concerns with Reynolds and Kamphaus' (2003) analyses

Several methodological concerns surround the analyses conducted by Reynolds and Kamphaus (2003). When conducting EFA, the researcher must make two major decisions, which include deciding on the number of factors to extract and selecting a method for rotating the factors (Frazier & Youngstrom, 2007). For the first decision, many criteria exist for determining the number of factors to be extracted. Several criticisms have been made of the factor extraction criteria selected by Reynolds and Kamphaus. Frazier and Youngstrom argued that Cattell's (1966) scree test is a highly subjective method that often results in poor interrater agreement when used. Though frequently used, Kaiser's (1960) criterion is thought to be inadequate because it tends to lead to overfactoring (Fabrigar, Wegener, MacCallum, & Strahan, 1999). Two additional factor extraction criteria, Horn's parallel analysis (HPA; Horn, 1965) and Minimum Average Partial (MAP; Velicer, 1976) analysis, are more accurate in determining the number of factors to retain (Frazier & Youngstrom, 2007; Thompson & Daniel, 1996; Zwick & Velicer, 1986) and have been recommended as preferred criteria for factor extraction (Velicer, Eaton, & Fava, 2000).

A second methodological concern of Reynolds and Kamphaus' (2003) analyses is their selection of an orthogonal rotation method to rotate the retained factors to simple structure. Oblique rotations were not reported by Reynolds and Kamphaus despite the frequently observed strong correlations between verbal and nonverbal intelligence measures (e.g., Kush, 1996; Macmann & Barnett, 1994). Moreover, the RIAS professional manual indicated a significant correlation between the VIX and NIX (r=.61). Tabachnik and Fidell (2007) suggested that when between factor correlations are .32 or higher, oblique rotations are warranted. Given both theoretical and empirical support for correlated RIAS factors, the necessity of examining oblique rotations is apparent. According to Fabrigar et al. (1999),

> Oblique rotations provide a more accurate and realistic representation of how constructs are likely to be related to one another. Thus, from a substantive perspective, the restriction of uncorrelated factors imposed by Varimax and other orthogonal rotations is often unwarranted and can yield misleading results. (p. 282)

Others have also argued for the suitability of oblique rotations when factors are substantially correlated, including Costello and Osborne (2005), Gorsuch (1983), and Thompson (2004).

A final concern is Reynolds and Kamphaus' (2003) neglect of higher-order factor analysis despite stating Carroll's hierarchical theory of intelligence was influential in the development of the RIAS. In the case of intelligence tests, higher-order factor analysis allows for the extraction of variance accounted for by general intelligence first. The remaining variance, which is free of all variance present in the general factor (McClain, 1996), is then assigned to the lower-order factors (e.g., verbal and nonverbal intelligence). Therefore, higher-order factor analysis takes into account the reality of correlated factors, but also allows for an examination of factor structure beyond the higher-order factor. The Schmid and Leiman (1957) procedure has been recommended for transforming correlated first-order factors and residualizing all first order variance present in the second order (general) factor (Carretta & Ree, 2001; Carroll, 1993, 1995, 1997, 2003; Gustafsson & Snow, 1997; McClain, 1996; Ree, Carretta, & Green, 2003; Thompson, 2004). This procedure "preserves the desired interpretation characteristics of the oblique solution, but also discloses the hierarchical structuring of the variables" (Schmid & Leiman, 1957, p. 53). Such oblique solutions are essential for reporting and understanding correlated factors as is typically observed in measures of intelligence. Additionally, the Schmid and Leiman procedure allows for examination of the amount of variance explained by the first and second order factors.

Purpose of study

Beyond the standardization sample, no empirical studies examining the factor structure of the RIAS have been reported. The purpose of the current study was to examine the factor structure of the RIAS with a large sample of students referred for evaluations to determine eligibility for educational services beyond regular education. In order to understand the factor structure of the RIAS more thoroughly, the current study used (1) more rigorous factor extraction criteria (HPA and MPA), (2) EFAs with oblique and orthogonal rotations, and (3) higher-order factor analyses. Although using CFA to test the possible theoretical models examined during test standardization was considered, the approach taken in the current study is more aligned with recommendations provided in the factor analysis literature (e.g., Fabrigar et al., 1999; Frazier & Youngstrom, 2007; Gorsuch, 1983; Velicer, et al., 2000). A major problem that can occur from using CFA-based indices is the retention of more factors than data merit. Although CFA is currently a popular technique, Frazier and Youngstrom argued it is likely being overly relied upon during test development. In their study of the major intelligence tests, these researchers found these tests had been highly overfactored and the tendency toward overfactoring had worsened over the last decade. Clearly, CFA has a valuable place within test development; however, due to the problems associated with the methods used by Reynolds and Kamphaus (2003), allowing the data to drive the analysis through EFA and higher-order factor analysis is arguably more appropriate than model-testing using CFA.

Research questions

The three research questions of the current study were (1) Using multiple criteria for factor extraction, including HPA and MAP, how many RIAS factors should be retained?; (2) What is the factor structure of the RIAS using oblique and orthogonal rotations?; and (3) What is the hierarchical factor structure of the RIAS and what proportion of variance is associated with each factor when higher-order factor analyses are used?

Method

Participants

Participants were 1163 students enrolled in a large urban/suburban public school system (approximately 75,000 students) in a mid-Atlantic state. They ranged in age from 6 to 18 years (M=9.67, SD=2.61) and were in grades kindergarten through 12. Table 1 presents detailed demographic data for the sample. All participants were administered the RIAS as part of the eligibility determination protocol for either special education or gifted services. Participants were selected regardless of multidisciplinary evaluation team decision, and thus included those who qualified for special education or gifted services and those who did not. Participants considered for special education eligibility were referred by school-based multidisciplinary teams due to significant academic underachievement. The members of this portion of the sample included (1) those referred for an initial evaluation as part of the eligibility determination process and (2) those referred for re-evaluation as part of the triennial reevaluation of special education placement. Special education classification was determined by multidisciplinary evaluation teams using the state and federal requirements (Individuals with Disabilities Education Act of 1997) in place at the time of the evaluation. Participants referred for gifted evaluations were referred by parents and/or teachers due to notably high academic achievement. Final decisions regarding gifted eligibility were not part of the current data set.

Table 1
Sample demographic characteristics ($N = 1163$)

Variable	n	%
Sex		
Male	717	61.7
Female	446	38.3
Race/ethnicity		
African American	405	34.8
White	619	53.2
Hispanic	47	4.0
American Indian	17	1.5
Asian	56	4.8
Native Hawaiian	1	0.1
Missing data	18	1.5
Grade		
Kindergarten	11	0.9
1	133	11.4
2	243	20.9
3	240	20.6
4	155	13.3
5	121	10.4
6	64	5.5
7	50	4.3
8	49	4.2
9	44	3.8
10	25	2.1
11	12	1.0
12	6	0.5
Missing data	10	0.9
Disability/exceptionality		
Specific learning disability	538	46.3
Emotional disorder	58	5.0
Mental retardation	9	0.8
Regular education/not disabled	173	14.9
Traumatic brain injury	1	0.1
Other health impairment	100	8.6
Speech/language impairment	8	0.7
Autism	7	0.6
Significant developmental delay	8	0.7
Multiply disabled	2	0.2
Visual impairment	1	0.1
504	4	0.3
Orthopedic impairment	3	0.3
Withdrew from eligibility determination process	4	0.3
Gifted	235	20.2
Missing data	12	1.0

Instrument

The RIAS is an individually administered intelligence test for persons between the ages of 3 and 94. It is composed of a two-subtest measure of verbal intelligence (i.e., the

VIX) and a two-subtest measure of nonverbal intelligence (i.e., the NIX). An overall score (i.e., the CIX) is calculated from the sum of the *T* scores of all four subtests and thus provides an estimate of global intelligence (*g*) that includes both verbal and nonverbal abilities. The two subtests that compose the VIX include Guess What (GWH) and Verbal Reasoning (VRZ). On the GWH subtest, examinees attempt to identify an object or concept through the use of two to four verbally presented clues. The VRZ subtest requires examinees to complete verbal analogies using one or two words. The two subtests that compose the NIX include Odd-Item Out (OIO) and What's Missing (WHM). On the OIO subtest, examinees are shown a card with five to seven pictures and are asked to identify the one that does not go with the others. The WHM subtest requires examinees to identify the missing element within a presented picture.

The RIAS also includes a co-normed supplemental memory measure composed of two subtests — one verbal and one nonverbal. The CMX is calculated from the sum of the *T* scores of the two subtests and purportedly provides an estimate of overall memory ability. On the Verbal Memory subtest (VRM), brief stories are read aloud to examinees who subsequently attempt to recall them. Examinees are exposed to a target picture for 5 s on the Nonverbal Memory subtest (NVM) and then required to identify it within a group of pictures.

The standardization sample of the RIAS included 2438 individuals and was representative of the United States population according to age, gender, ethnicity, educational attainment, and geographical region (see Reynolds & Kamphaus, 2003). Subtest scores are presented in the form of *T* scores ($M=50$, SD = 10). The VIX, NIX, CMX, and CIX are presented in the form of standard scores ($M=100$, SD = 15). Extensive internal consistency, temporal stability, and inter-rater agreement data are reported and indicate relatively high reliability of scores that is invariant across age, gender, and ethnicity.

Procedure

Data used in the current study were archival and drawn from a database used to store demographic and assessment information for all students evaluated by school psychologists within the school system from October 2003 to March 2005. The variables selected included RIAS CIX, VIX, NIX, CMX, subtest scores, and demographic data (i.e., age, grade, ethnicity, gender, and special education category [when relevant]). Each RIAS was individually-administered at the participant's school by state certified school psychologists or school psychologist interns.

Data analyses

Multiple criteria as recommended by Gorsuch (1983) were used to determine the number of factors to extract and included Kaiser's (1960) criterion, Cattell's (1966) scree test, HPA, and MAP. Theoretical consideration was also used in determining the number of factors to extract and explore. Random data and resulting eigenvalues for PA were produced using the *Monte Carlo PCA for Parallel Analysis* computer program (Watkins, 2000) with 100 replications to provide stable eigenvalue estimates. MAP analyses were conducted as programmed for SPSS by O'Connor (2000).

The present study utilized the principal axis method of EFA of the RIAS four- and six-subtest correlation matrices, as this was the method used and reported in the RIAS professional manual for the standardization sample (Reynolds & Kamphaus, 2003). EFA was conducted for the four-subtest (GWH, OIO, VRZ, WHM) and six-subtest (GWH, OIO, VRZ, WHM, VRM, NVM) configurations. Varimax and Promax rotations were both examined and reported in the present study. Both factor *structure* and *pattern* coefficients are reported. Factor structure coefficients illustrate the relationships between variables and factors along with the relationship between variables and the common variance among factors (Tabachnik & Fidell, 2007). Factor pattern coefficients represent weights for calculation of factor scores rather than correlations between the subtests and factors represented by structure coefficients (Thompson, 2004). The more correlated the factors in an oblique solution, the more divergent factor pattern and factor structure coefficients become and the greater the need for examination of higher-order structure (Thompson).

The Schmid and Leiman (1957) procedure was used to examine the hierarchical factor structure of the RIAS when extracting more than one factor. Following Gorsuch (1983), iterations in first-order factor extraction were limited to two. The resulting factors were

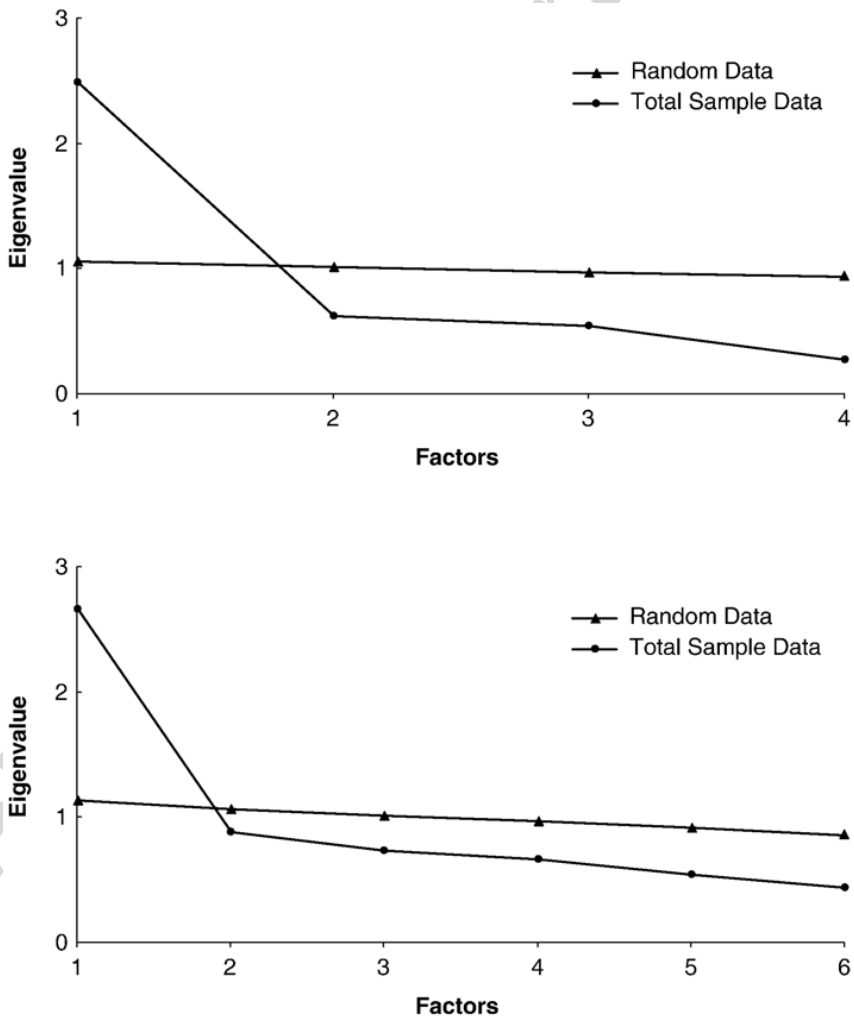

Fig. 1. Scree plots for RIAS parallel analyses.

Table 2
Intercorrelations between the four RIAS subtest scores for total sample (N=1163)

	M	SD	GWH	VRZ	OIO	WHM
Guess What (GWH)	48.02	10.52				
Verbal Reasoning (VRZ)	51.98	9.33	.67			
Odd-Item Out (OIO)	48.62	12.02	.48	.49		
What's Missing (WHM)	51.62	10.97	.45	.44	.44	

Note. All correlations were statistically significant (p<.01).

orthogonalized using the Schmid and Leiman procedure as programmed in the MacOrtho computer program (Watkins, 2004).

Results

Factor extraction criteria analyses

All factor extraction criteria suggested extracting only one factor for both the four- and six-subtest RIAS configurations. Only one factor had an eigenvalue greater than one (see Tables 4 and 5 and Fig. 1). Visual inspection of both scree plots (see Fig. 1) also indicated one factor. Scree plots for HPA are presented in Fig. 1 and illustrate one viable factor for these data. MAP also indicated extraction of only one factor for both the four- and six-subtest RIAS configurations. The smallest average squared correlation was .13 for one component in the four-subtest RIAS configuration and .05 for one component for the six-subtest RIAS configuration.

Exploratory factor analyses

Exploratory factor analyses were conducted using two separate correlation matrices. All analyses examining the four-subtest configuration were conducted using the correlation matrix for the total sample (see Table 2). Only a portion of the total sample (N=551) was administered the two additional memory subtests. Therefore, all analyses examining the six-subtest configuration were conducted using the correlation matrix shown in Table 3.

Tables 4 and 5 present the factor coefficients of each of the subtests for the first unrotated factor (i.e., g-loadings) for the four- and six-subtest configurations, respectively. For the

Table 3
Intercorrelations between the six RIAS subtest scores (N=551)

	M	SD	GWH	VRZ	OIO	WHM	VRM	NVM
Guess What (GWH)	45.26	9.20						
Verbal Reasoning (VRZ)	44.87	9.53	.51					
Odd-Item Out (OIO)	49.99	8.65	.36	.38				
What's Missing (WHM)	49.68	10.79	.40	.37	.33			
Verbal Memory (VRM)	43.31	9.10	.37	.40	.22	.21		
Nonverbal Memory (NVM)	51.23	9.29	.26	.29	.30	.33	.21	

Note. All correlations were statistically significant (p<.01).

Table 4
Two-factor principal axis exploratory factor analysis of the RIAS four subtest configuration with Varimax and Promax rotations

Subtest	*g*-loading	Varimax structure coefficients		Promax pattern coefficients		Promax structure coefficients	
		I	II	I	II	I	II
GWH	.79	**.71**	.40	**.77**	.06	**.82**	**.67**
VRZ	.80	**.72**	.41	**.77**	.06	**.82**	**.67**
OIO	.64	.35	**.59**	.11	**.60**	**.58**	**.68**
WHM	.59	.31	**.56**	.06	**.60**	**.53**	**.64**
Eigenvalues		2.49	.63				
% Variance		51.69	3.74				

Note. RIAS = Reynolds Intellectual Assessment Scales, GWH = Guess What, OIO = Odd-Item Out, VRZ = Verbal Reasoning, WHM = What's Missing. *g*-loadings are factor structure coefficients from the first unrotated factor. Salient factor structure coefficients (>44) based on Comrey and Lee's (1992) classifications are presented in bold. Promax rotated Factor 1 and Factor 2 ($r = .79$).

one-factor solution, each of the subtests loaded saliently. The verbally-oriented intelligence subtests had the highest *g*-loadings, followed by the nonverbally-oriented intelligence subtests, and the memory subtests.

Four-subtest configuration

Although only one factor was indicated by all factor extraction criteria, two factors were extracted based on theoretical consideration and for direct comparison with results from the RIAS standardization sample. Using Varimax (orthogonal) rotation, all subtests were associated with the theoretically consistent factors as found in the RIAS standardization sample. Promax (oblique) rotation of the forced two-factor solution produced salient factor structure coefficients for each subtest for both factors (see Table 4). Factors I and II were highly correlated ($r = .79$). Factor pattern coefficients produced similar subtest associations

Table 5
Two-factor principal axis exploratory factor analysis of the RIAS six subtest configuration with Varimax and Promax rotations

Subtest	*g*-loading	Varimax structure coefficients		Promax pattern coefficients		Promax structure coefficients	
		I	II	I	II	I	II
GWH	.69	**.58**	.38	**.57**	.15	**.69**	**.59**
VRZ	.72	**.66**	.36	**.69**	.07	**.75**	**.60**
VRM	.48	**.52**	.17	**.62**	−.10	**.54**	.37
OIO	.54	.30	**.47**	.12	**.46**	**.48**	**.56**
WHM	.56	.25	**.58**	−.01	**.64**	**.48**	**.63**
NVM	.45	.18	**.48**	−.05	**.55**	.37	**.51**
Eigenvalues		2.67	.89				
% Variance		34.78	3.89				

Note. RIAS = Reynolds Intellectual Assessment Scales, GWH = Guess What, OIO = Odd-Item Out, VRZ = Verbal Reasoning, WHM = What's Missing, VRM = Verbal Memory, NVM = Nonverbal Memory. *g*-loadings are factor structure coefficients from the first unrotated factor. Salient factor structure coefficients (>.44) based on Comrey and Lee's (1992) classifications are presented in bold. Promax rotated Factor 1 and Factor 2 ($r = .76$).

with factors to those obtained in the orthogonal rotation. The highly correlated factors illustrated by the divergent factor structure coefficients do not suggest distinct factors and warrant higher-order factor extraction and examination.

Six-subtest configuration

Based on theoretical consideration and for comparison with the results from the standardization sample, two and three factors were extracted using the six-subtest configuration. Table 5 presents the results of the forced two-factor extraction with Varimax and Promax rotations. When Varimax rotation was used, factor structure coefficients were generally consistent with the theoretical model and those reported from the standardization sample. Promax rotation produced salient factor structure coefficients for all subtests (except the NVM subtest) for the first factor and salient factor structure coefficients for all subtests (except the VRM subtest) for the second factor (see Table 5). The correlation between Factors I and II was .77 and indicated highly correlated factors. Even with the additional memory subtests, separate factors did not emerge. Factor pattern coefficients were similar to those obtained in the orthogonal rotation. As with the four-subtest configuration, these results do not suggest distinct factors.

When three factors were extracted and Varimax rotation was used, different subtest factor associations occurred than that found with the standardization sample. Table 6 shows that the GWH, VRZ, and WHM subtests were associated with the first factor. The VRZ subtest cross-loaded on the second factor and joined with the VRM subtest to help define the second factor. Only the NVM subtest had a salient factor structure coefficient for the third factor. Promax rotation of the three-factor solution resulted in the four core subtests having salient factor structure coefficients for the first factor. The GWH and VRZ subtests cross-loaded on the second factor and joined the VRM subtest to help define the second factor. The WHM cross-loaded on Factor III and was joined by the NVM subtest to help

Table 6
Three-factor principal axis exploratory factor analysis of the RIAS six subtest configuration with Varimax and Promax rotations

Subtest	Varimax structure coefficients			Promax pattern coefficients			Promax structure coefficients		
	I	II	III	I	II	III	I	II	III
GWH	**.60**	.39	.14	**.68**	.14	−.11	**.71**	**.57**	.30
VRZ	**.52**	**.46**	.20	**.51**	.27	−.08	**.70**	**.62**	.35
VRM	.18	**.61**	.14	−.04	**.66**	.06	.44	**.65**	.23
OIO	.43	.17	.31	.48	−.04	.16	**.54**	.34	.41
WHM	**.49**	.12	.36	**.57**	−.14	.19	**.58**	.31	**.46**
NVM	.19	.15	**.61**	.04	.08	**.60**	.42	.29	**.64**
Eigenvalues	2.67	.89	.74						
% Variance	35.27	5.16	2.69						

Note. RIAS = Reynolds Intellectual Assessment Scales, GWH = Guess What, OIO = Odd-Item Out, VRZ = Verbal Reasoning, WHM = What's Missing, VRM = Verbal Memory, NVM = Nonverbal Memory. *g*-loadings are factor structure coefficients from the first unrotated factor. Salient factor structure coefficients (>.44) based on Comrey and Lee's (1992) classifications are presented in bold. Promax rotated Factor 1 and Factor 2 (r = .69), Promax rotated Factor 1 and Factor 3 (r = .55), Promax rotated Factor 2 and Factor 3 (r = .30).

define the third factor. Promax factor pattern coefficients resembled the Varimax factor structure coefficients.

Schmid–Leiman analyses

Four-subtest configuration

Schmid–Leiman results for the four-subtest configuration are presented in Table 7. The second-order (*g*) factor accounted for 33% to 55% of the RIAS subtest variance, the largest portion of total variance (44.94%) and the largest portion of common variance (87.00%). The Verbal factor accounted for 4.40% of the total variance and 8.53% of common variance beyond the general factor, whereas the Nonverbal factor accounted for 2.31% of the total variance and 4.47% of common variance beyond the general factor. All subtests were associated with theoretically consistent factors; however, the first-order factor coefficients were low for both factors.

Six-subtest configuration

Schmid–Leiman results for the six-subtest configuration and two-factor extraction are presented in Table 8. The second-order (*g*) factor accounted for 19% to 43% of the RIAS subtest variance, the greatest portion of the total variance (29.90%), and greatest portion of common variance (80.36%). The Verbal factor accounted for 3.98% of the total variance and 10.70% of common variance beyond the general factor, whereas the Nonverbal factor accounted for 3.33% of the total variance and 8.94% of common variance beyond the general factor. Again, all subtests were associated with theoretically consistent factors, but the first-order factor structure coefficients were low for both factors. Because of a lack of support for a three-factor model, results for the Schmid–Leiman analysis are not reported for the three-factor extraction.

Discussion

The purpose of this study was to examine the factor structure of the RIAS in an independent sample by replicating and extending the EFAs conducted by Reynolds and

Table 7
Factor structure coefficients and variance sources for the RIAS four-subtest configuration based on the orthogonalized higher-order factor model

Subtest	General intelligence		Verbal		Nonverbal			
	b	$\%S^2$	b	$\%S^2$	b	$\%S^2$	h^2	u^2
GWH	0.73	54	0.29	8	0.04	0	0.63	0.37
VRZ	0.74	55	0.29	8	0.04	0	0.63	0.37
OIO	0.62	39	0.07	0	0.21	4	0.43	0.57
WHM	0.58	33	0.05	0	0.21	5	0.38	0.62
% Total S^2		44.94		4.40		2.31	51.65	48.35
% Common S^2		87.00		8.53		4.47	–	–

Note. RIAS = Reynolds Intellectual Assessment Scales, GWH = Guess What, VRZ = Verbal Reasoning, OIO = Odd-Item Out, WHM = What's Missing, b = factor structure coefficient (loading), h^2 = communality, u^2 = uniqueness.

Table 8
Factor structure coefficients and variance sources for the RIAS six subtest configuration based on the orthogonalized higher-order factor model

Subtest	General intelligence		Verbal		Nonverbal			
	b	$\%S^2$	b	$\%S^2$	b	$\%S^2$	h^2	u^2
GWH	0.64	40	0.26	7	0.07	0	0.48	0.52
VRZ	0.66	43	0.29	8	0.05	0	0.52	0.48
VRM	0.46	21	0.29	8	− 0.05	0	0.29	0.71
OIO	0.52	27	0.04	0	0.23	5	0.32	0.68
WHM	0.54	29	0.01	0	0.27	7	0.36	0.64
NVM	0.44	19	−0.03	0	0.26	7	0.26	0.74
% Total S^2		29.90		3.98		3.33	37.21	62.79
% Common S^2		80.36		10.70		8.94	–	–

Note. RIAS = Reynolds Intellectual Assessment Scales, GWH = Guess What, VRZ = Verbal Reasoning, VRM = Verbal Memory, OIO = Odd-Item Out, WHM = What's Missing, NVM = Nonverbal Memory, b = factor structure coefficient (loading), h^2 = communality, u^2 = uniqueness.

Kamphaus (2003). Additional analyses beyond those conducted by Reynolds and Kamphaus were used to investigate the RIAS factor structure more thoroughly. These additional analyses included the use of rigorous factor extraction criteria (i.e., HPA and MPA), oblique rotations upon extracting the factors, and higher-order factor analyses. Reynolds and Kamphaus suggested the RIAS is a psychometrically sound measure of general intelligence, verbal intelligence, and nonverbal intelligence, and that the composites (CIX, VIX, and NIX) purportedly measuring these constructs can be interpreted accordingly. They indicated less confidence in the interpretation of the memory composite (CMX). According to the *Standards for Educational and Psychological Testing* (AERA, APA, & NCME, 1999), interpretive methods need to be validated in order to be used by practitioners. Replication of the RIAS factor structure in independent samples is critical for making judgments about the validity of Reynolds and Kamphaus' interpretation recommendations. Investigation of the RIAS, in particular, is important because its brief nature may lead to wide-scale adoption by practitioners working in schools (Elliott, 2004).

In their examination of the standardization data, Reynolds and Kamphaus (2003) reported eigenvalues and scree plots were investigated to determine the number of factors that could be viably extracted. Although Reynolds and Kamphaus do not provide these data in the RIAS professional manual, they suggested that both two- and three-factor solutions were viable. Both factor extraction criteria selected by Reynolds and Kamphaus are considered lenient and may lead to overfactoring (Frazier & Youngstrom, 2007). HPA and MPA are more rigorous and accurate factor extraction criteria (Zwick & Velicer, 1986). In the current study, examination of Kaiser's (1960) criterion, Cattell's (1966) scree test, HPA, and MPA all indicated the extraction of only one factor. Therefore, attempting to extract more than one factor from these data would be considered overfactoring.

The loadings of the first unrotated factor represent the one-factor solution (i.e., g). Using the four core subtests, the verbally oriented subtests (GWH and VRZ) had higher g-loadings than the nonverbally oriented subtests (OIO and WHM). Kaufman (1994) proposed that g-loadings above .70 are "good," those between .50 and .69 are "fair," and those below .50 are "poor." Based on Kaufman's classification system, the *g*-loadings of the verbally oriented subtests were "good," whereas the *g*-loadings of the nonverbally oriented subtests were "fair." The lower *g*-loadings of the WHM and OIO subtests were consistent with the pattern found with the standardization data. When the two memory subtests were added to the analyses, only the VRZ subtest had a "good" *g*-loading, and the GWH subtest approached this classification (.69). The remaining subtests had *g*-loadings below .70, with the memory subtests having *g*-loadings in the "poor" range. As Bracken (2005) pointed out in his review of the RIAS, the GWH and VRZ subtests appear to be the only subtests that provide consistent measures of general intelligence.

Despite the multiple factor extraction criteria indicating only one factor, both two- and three-factor solutions were explored based on theoretical consideration and for comparison with the results of the RIAS standardization sample. For the two-factor solutions with both the four- and six-subtest configurations using orthogonal rotation, the subtests were associated with the same factors as they were with the standardization sample. Additionally, the subtest factor structure coefficients for each factor were generally of the same magnitude as those found with the standardization sample.

The use of oblique rotation resulted in substantially different results than when orthogonal rotation was used. For both two-factor solutions, considerable subtest cross-loadings occurred. The two factors in both the four- and six-subtest configurations were highly correlated (.79 for the four-subtest configuration and .76 for the six-subtest configuration). These high correlations between the factors explain the divergent factor structure coefficients of the orthogonal and oblique rotations because oblique rotation incorporates the correlations between the factors and orthogonal does not. It should be underscored, again, that when correlations between factors are larger than .32, oblique rotation is warranted (Tabachnik & Fidell, 2007). Substantial cross-loading in oblique rotation structure coefficients was consistent with the results of the factor extraction criteria analyses. These results are likely due to attempting to extract more factors than was justified by these data. One explanation as to why distinct factors were not found in the current data is the possibly insufficient number of subtests used to define the factors. At least three indicators per factor are recommended for identifying factors (Fabrigar et al., 1999; Kline, 2005).

When the three-factor solution was explored, some subtests migrated to different factors than they were assigned in the standardization sample when both orthogonal and oblique rotation were used. The results of the three-factor solution illuminate problems with the validity of the memory composite in particular. Reynolds and Kamphaus (2003) suggested that practitioners should proceed with caution in interpreting the memory composite and recommended that more research be conducted to determine the viability of the memory composite as a distinct factor. In their use of confirmatory factor analysis to examine the three-factor solution, Reynolds and Kamphaus concluded, "The CMX is supported by some factor analytic evidence, but it does not appear to exist routinely as a distinct factor from the VIX and NIX" (p. 51). The present results do not provide factor analytic evidence of the existence of a memory factor. The VRM and NVM subtests were clearly associated with different factors in this sample.

The substantial correlation between the RIAS factors suggested a higher-order factor (Gorsuch, 1983; Thompson, 2004). The Schmid and Leiman (1957) procedure allowed for the removal of the variance accounted for by the higher-order factor. Once the variance accounted for by general intelligence was partialled out, the subtests were assigned to theoretically consistent factors for the two-factor solutions using both four and six subtests. Despite theoretically consistent factor associations for the two-factor solutions, the largest amount of variance was accounted for by the higher-order, general intelligence factor. The factors representing verbal and nonverbal intelligence accounted for small increases in explained variance.

Implications for practice

The findings of the current study suggest the following conclusions regarding the use of the RIAS memory, verbal, nonverbal, and composite scores with similarly referred individuals. The most obvious implication for practice drawn from these results is that those using the RIAS with similarly referred individuals should not interpret the memory composite as if it represents a distinct factor. Factor analyses from the RIAS standardization sample provided tentative evidence at best for the viability of a distinct memory factor. The current results do not provide evidence for a distinct memory factor. It is recommended that practitioners avoid making interpretations of the CMX in a manner that is suggestive of a general memory construct. Reynolds and Kamphaus (2003) also suggested that it is best to exclude the two memory subtests in the measurement of general intelligence. The results of this study support this recommendation given the poor *g*-loadings of the NVM and VRM subtests.

A second implication drawn from this study relates to a question that will likely be on the minds of most practitioners, “Is the RIAS a better instrument than others for measuring general intelligence?” In his review of the RIAS, Schraw (2005) concluded the answer to this question is unclear and urged researchers to conduct further investigation. The present results suggest that only two of the four subtests (GWH and VRZ) had good *g*-loadings, whereas the nonverbally-oriented subtests had fair *g*-loadings. Despite Reynolds and Kamphaus’ (2003) admirable goal of eliminating the need for motor coordination and visual–motor speed on the nonverbal components of the RIAS, the sacrifice appears to result in a weaker measure of general intelligence. Bracken (2005) argued that one of the nonverbal subtests, WHM, is largely the same as the Wechsler Picture Completion subtest, which traditionally has produced only fair *g*-loadings (.60 on the WISC-III and WISC-IV) and was reassigned from the core battery to the supplemental battery of the WISC-IV.

The final practical implication drawn from these results relates to the interpretive weight that should be given to the CIX, VIX, and NIX. These findings suggest that, when working with similarly referred students, the CIX should be given the predominance of interpretive weight. Giving considerable interpretative weight to the VIX and NIX appears questionable because the amount of variance explained by these factors is minimal once the variance accounted for by general intelligence is partialled out. The law of parsimony applies here in that a simpler explanation of the structure is preferred given the small amount of variance added by the first-order (Verbal and Nonverbal) factors once the higher-order (*g*) factor is considered.

Limitations

The present study’s limitations are related to generalizability. Because a referred sample was used, it is unknown whether these findings are generalizable to the population at large.

Additionally, this sample consisted of considerably more male than female participants and the sample's ethnic distribution was not representative of the country at large. Finally, this sample was drawn from one geographic area of the country and therefore is not representative of the entire United States.

Conclusions

The development of the RIAS was founded upon admirable goals such as the provision of a time- and cost-efficient measure of intelligence that reduces dependence on motor coordination and visual–motor speed. Results of the present study indicated that the most valid use of the RIAS with similarly referred individuals is as an estimate of general intelligence. It would be beneficial for future research to investigate further the RIAS with other samples to determine its validity more adequately.

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