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Construct Validity of the WAIS–5: Complementary Exploratory and Confirmatory Factor Analyses of the 20 Primary and Secondary Subtests

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Abstract

The Wechsler Adult Intelligence Scale-Fifth Edition (WAIS–5; Wechsler, 2024) latent factor structure was assessed using complementary hierarchical exploratory factor analyses (EFA) with the Schmid and Leiman (1957) procedure and confirmatory factor analyses (CFA) using the standardization sample (*N* = 2,020) correlation matrix and descriptive statistics of the 20 primary and secondary WAIS–5 subtests. EFA results did not support five latent factors with separate Visual Spatial and Fluid Reasoning factors. Instead, a four-factor model with Visual Spatial and Fluid Reasoning factors merged into the former Perceptual Reasoning factor and measurement dominated by a general intelligence (*g*) factor—similar to the WAIS–IV structure—was supported. CFA results indicated that a bifactor model with four group factors provided the best fit, consistent with the EFA findings. Overall, the EFA and CFA results did not support the purported WAIS–5 structure and instead replicated findings from independent assessments of the WISC–V with standardization and clinical samples, that indicated primary, if not exclusive, interpretation of the FSIQ as an estimate of psychometric *g*.

Keywords: WAIS–5, exploratory factor analysis, confirmatory factor analysis, bifactor model, hierarchical CFA, intelligence

Construct Validity of the WAIS–5: Complementary Exploratory and Confirmatory Factor Analyses of the 20 Primary and Secondary Subtests

Wechsler intelligence scales in general, and the Wechsler Adult Intelligence Scale (WAIS) in particular, have been extremely popular among clinicians for clinical assessment of adolescents and adults (Alfonso et al., 2000; Alfonso & Pratt, 1997; Belter & Piotrowski, 2001; Benson et al., 2019; Goh et al., 1981; Hutton et al., 1992; Kaufman & Lichtenberger, 2000; Pfeiffer et al., 2000; Stinnett et al., 1994; Watkins et al., 1995). In fact, previous versions of the WAIS have been regarded as the "gold standard" in intelligence testing and one of the most frequently administered measures in applied psychology (Camara et al., 2000; Ivnik et al., 1992). Over time, numerous international adaptations and standardizations of various Wechsler versions have also been published.

The Wechsler Adult Intelligence Scale-Fifth Edition (WAIS–5; Wechsler, 2024) is the latest version that was recently published as a revision of the Wechsler Adult Intelligence Scale-Fourth Edition (WAIS–IV; Wechsler, 2008a). Like the Wechsler Intelligence Scale for Children-Fifth Edition (WISC–V; Wechsler, 2014a), the WAIS–5 purports to measure general intelligence (*g*) as a higher-order construct and five, first-order group factor (broad ability) constructs: Verbal Comprehension (VC), Visual Spatial (VS), Fluid Reasoning (FR), Working Memory (WM), and Processing Speed (PS). Thus, like the WISC–V, and as foreshadowed by Weiss et al. (2013a, 2013b), the WAIS–5 attempted to split the former Perceptual Reasoning (PR) factor into separate VS and FR dimensions to measure five, first-order latent factors. The WAIS–5 also now includes 15 Ancillary Index scores including five Expanded Index Scores, six Domain-Specific Index Scores, and four Summary Index Scores produced from the 10 primary and 10 secondary subtests. In addition to various changes in administration and scoring, two WAIS–IV subtests

(Picture Completion and Cancellation) were deleted and five new subtests (Running Digits, Set Relations, Naming Speed Quantity, Symbol Span, and Spatial Addition) were added. Whereas in previous WAIS editions several Digit Span tasks (Digits Forward, Digits Backward, Digits Sequencing) were combined into a single Digit Span subtest score, now each represents a separate subtest.

Although the *Standards for Educational and Psychological Testing* (Standards; AERA et al., 2014) are cited as a guiding framework throughout the revision processes, the WAIS–5 *Technical and Interpretive Manual* ([hereafter, Technical Manual] Wechsler et al., 2024) contains numerous shortcomings. In particular, the omission of critical psychometric information prevents users from evaluating the validity of Wechsler et al. interpretive claims, determining the adequacy of recommended score comparisons, or making decisions regarding evidence-based test interpretation. For example, internal consistency estimates provided for subtests are split-half coefficients (except for speeded subtests where test-retest stability coefficients were used); however, this approach conflates multidimensional subtest variance sources into a single true-score variance estimate. Biased estimates of reliability may be obtained when statistical assumptions are not satisfied and this is especially salient when using split-half and alpha coefficients in intelligence tests (Cho & Kim, 2015; Green & Hershberger, 2000). Instead, model-based reliability estimates are preferred to disclose the sources of true score variance (Gignac & Watkins, 2013; Watkins, 2017). Further, the WAIS–5 Technical Manual does not provide reliability estimates for various difference scores which form the basis for clinical interpretation of factor index score and subtest score ipsative (person-centered) strengths and weaknesses or for subtest level or ancillary level pairwise comparisons. Short-term (M = 29 days, range [12, 124]) test-retest reliability (stability) of subtests, index scores, and ancillary scores are reported for various standardization subgroups (all ages, 16-34, 35-39, 70-90) and included stability coefficients, corrected coefficients, and standard differences (effect sizes) across the retest interval. While generally favorable, notably absent are stability coefficients or estimates for strengths and weaknesses derived from the ipsative and pairwise comparisons. Watkins et al. (2022) documented long term *instability* of such ipsative WISC–V strengths and weaknesses which operated at chance in a clinical sample, but to date such investigations with normative samples (short- and long-term) have not been published. It is too early in the WAIS–5 life cycle for long-term stability studies to be available.

Structural validity evidence of tests is critical because it justifies the scoring structure of the test. Structural validity evidence presented in the WAIS–5 Technical Manual, like the WAIS–IV and WISC–V before it, reported only confirmatory factor analyses (CFA). Wechsler et al. (2024) justified this decision by reiterating their preference for CFA over exploratory factor analysis (EFA) when examining an explicit theoretical structure or comparing competing models, despite substantial changes to the test including the removal of two previous subtests, addition of five new subtests, the splitting of Digit Span tasks into separate subtests, modifications to instructions and scoring procedures, and the use of a new normative sample. Given such extensive changes it seems unlikely one could adequately anticipate all plausible models to test or subtest associations with latent factors, which provides a compelling rationale for beginning with EFA (Carroll, 1995; Reise, 2012) as it is an unrestricted factor analytic method that allows "data to speak for themselves" (Carroll, 1995, p. 436). EFA examines the interrelationships among subtest indicators without imposing preconceived structure (beyond specifying the number of factors to extract); and can elucidate structural issues, reducing the need for CFA post hoc model modifications and the problems associated with such adjustments. Najera et al. (2025) in their assessment of EFA and CFA methods concluded,

> First, given that confirmatory and exploratory techniques have opposed strengths and weaknesses, a safe practice when conducting a validation study would consist in analyzing the data with one of each and then evaluate to what extent the results of both approaches are congruent (p. 35).

As will be demonstrated, this is a crucial analytical process would have been beneficial when Wechsler et al. initially examined the internal structure of the WAIS–5.

Precursor Validity Research

In discussing previous WAIS–IV structural validity research, Wechsler et al. (2024) noted merit of an alternative WAIS–IV five-factor structure based on three studies (Benson et al., 2010; Sudarshan & Bowden, 2023; Weiss et al., 2013). What was not reported were the methodological and statistical details in each of these studies that significantly qualify their "merit." While Benson et al. and Weiss et al. examined higher-order models, Sudarshan and Bowden examined oblique models that had high factor correlations in all subsamples implying a higher-order general ability or a bifactor general dimension which were not considered. Benson et al. examined higher-order WAIS–IV representations with four and five first-order factors using summary statistics from the WAIS–IV *Technical and Interpretive Manual* (Wechsler, 2008b) to create a calibration sample and a validation sample. While the four-factor higher-order (Wechsler) model showed adequate fit with the calibration sample, the five-factor higher-order (CHC) model showed good fit which was also superior in global model fit. However, Benson et al. (2010) reported that the initial five-factor higher-order model from the calibration sample contained a standardized parameter estimate of 1.0 from *g* to G*f* (FR) which indicated empirical redundancy of G*f* (FR) and therefore suggested questionable inclusion of the G*f* (FR) dimension. Various cross-loadings were introduced to improve global model fit and the final cross-validation model was the five-factor higher-order (CHC) model that also included cross-loading of Arithmetic on both G*f* (FR) and G*sm* (WM). Inclusion of the Arithmetic cross-loading reduced the standardized parameter estimate of *g* to G*f* (FR) to .99, failing to negate questions regarding the viability of a separate G*f* (FR) dimension.

Wechsler et al. (2024) also provided no details regarding the Weiss et al. study which was the subject of a special journal issue where numerous methodological and statistical challenges were outlined by Canivez and Kush (2013). In order for Weiss et al. to get five first-order factors to work with their higher-order representation, it was necessary to add an intermediary Quantitative Reasoning (QR) factor between G*f* (FR) and the Figure Weights and Arithmetic subtests (which also cross-loaded on G*v* and G*sm*, respectively). A third cross-loading introduced was Matrix Reasoning on G*v* and G*f*. Even with those substantial post-hoc model modifications that appear to have been statistically rather than theoretically derived, the standardized parameter estimate of *g* to G*f* (FR) was again .99 and the standardized parameter estimate from G*f* (FR) to QR was .94, indicating continued poor discriminant validity (Brown, 2015; Kline, 2016).

Review of WAIS–IV structural validity literature prior to development of the WAIS–5 appears to be quite selective as Wechsler et al. (2024) did not reference or review several peer reviewed WAIS–IV studies illustrating EFA and CFA approaches with the standardization sample (Canivez & Watkins, 2010a, 2010b; Frisby & Beaujean, 2015) and a referred clinical sample (Nelson et al., 2013). For example, WAIS–IV EFA of the common subtests for the major age groups in the standardization sample (16-90, 16-69, 70-90) produced similar results indicating that while four factors could be identified and extracted, their moderate to high correlations resulted in a second-order EFA with Schmid and Leiman transformation (SLT; 1957) that illustrated dominance of the general intelligence dimension with only small portions of residual variance at the first-order (group factor) level (Canivez & Watkins, 2010a). WAIS–IV EFA for the adolescent age group (16-19) also found moderate to high factor correlations when extracting four first-order factors and second-order EFA with SLT partitioned the majority of variance to the higher-order *g* factor and small portions of residual variance to the four first-order (group) factors. Nelson et al. found, in a referral sample of college students ($N = 300$), that CFA of the 10 WAIS–IV primary subtests yielded no meaningful differences between oblique, indirect hierarchical (higher-order), or direct hierarchical (bifactor) representations with four group factors. Further assessment of the direct hierarchical (bifactor) model replicated standardization sample EFA results with the majority of variance being apportioned to the general (*g*) factor and small portions of variance in the four first-order (group) factors. Nelson et al. also reported model-based reliability estimates of omega-hierarchical (ω_H) for the *g* factor (.737) and omega-hierarchical subscale (ω_{HS}) for the group factors (.107 [PR]–.638 [PS]), indicating that a unit-weighted index based on all indicators for *g* would be reasonably well indexed and that of the four factor index scores only the PS factor met the minimum standard for possible interpretation (e.g., Reise, 2012). These studies included important findings that should have seemingly informed Wechsler et al. about rival models worthy of examination as well as methods and estimates that would help adjudicate WAIS–5 construct validity.

Incremental validity of WAIS–IV factor index scores in predicting performance on the Wechsler Individual Achievement Test-Second Edition (WIAT–II; Psychological Corporation, 2002) and Wechsler Individual Achievement Test-Third Edition (WIAT–III; NCS Pearson,

2009) beyond the FSIQ using the standardization linking sample (Canivez, 2013) also illustrated the dominance of *g* variance in the WAIS–IV where the FSIQ predicted medium to large portions of WIAT–II and WIAT–III scores. Factor index scores *uniquely* added typically trivial to small portions of additional prediction of WIAT–II and WIAT–III scores. Nelson et al. (2013) also examined incremental validity of WAIS–IV factor index scores in predicting achievement in the referred college sample mostly composed of students diagnosed with LD and/or ADHD. Nelson et al. reported results similar to Canivez (2013) with the WAIS–IV FSIQ typically accounting for largest portions of achievement test variance and the unique additional contribution of the factor index scores in predicting achievement was typically trivial to small.

Incremental validity studies reinforced the recommendation that principal interpretation of the WAIS–IV should be of the FSIQ. Kranzler et al. (2015) later reanalyzed the WAIS–IV standardization linking sample with the WIAT–II using a latent variable approach in explaining achievement variance from a bifactor representation of the WAIS–IV with four group factors. Kranzler et al. reported that psychometric *g* was the most important contributor to WIAT–II achievement but that VC contributed additional important explanations for some achievement domains (Word Reading, Reading Comprehension, Spelling, and Listening Comprehension subtests; Reading, Oral Language, and Total Achievement composite scores) with small to medium effect sizes. In sum, these replicated independent structural and predictive validity results for the WAIS–IV, combined with the internal validation research establishing the publisher preferred structural/interpretive for the test, provide a substantial foundation for the WAIS–5 structural revision (Dombrowski et al., 2025).

WAIS–5 Latent Factor Structure

Figure 1 presents a simplified version of the "optimal" WAIS–5 standardized measurement model presented by Wechsler et al. (2024, p. 81) and illustrates numerous problems. First, standardized factor paths from general intelligence (*g* [which was mislabeled "Full Scale" in the WAIS–5 Technical Manual]) to VS (.95) and to FR (.99) are extremely high and reflect poor discriminant validity (Brown, 2015; Kline, 2016). Second, Wechsler et al. included cross-loadings for Symbol Span (VS and WM), Spatial Addition (VS and WM), and Arithmetic (FR and WM). Such cross-loadings complicate the measurement model by abandoning simple structure (Thurstone, 1947) which is implied in the construction of unit-weighted composite scores. Third, Wechsler et al. included correlated errors of Running Digits and Digits Forward which also is of questionable practice unless there is a clear linear dependence between measures (Landis et al., 2009; MacCallum et al., 1992).

In the Wechsler et al. (2024) CFA, only higher-order models with five first-order (group) factors were compared and reported. There was no consideration of rival bifactor representations or models with fewer than the desired five group factors as implied by prior research. There was no specification of the statistical program (or its version) used to conduct CFA nor was there disclosure of the estimation method employed. Both omissions undermine basic scientific standards by impeding the ability to replicate—and even trust—the underlying analyses (Dombrowski, 2025; Dombrowski & McGill, 2024). CFA is entirely focused on model comparisons in the WAIS–5 Technical Manual based on global fit statistics and statistical comparisons between the models, but there are no presentations of standardized parameter estimates for any model other than the final measurement model 5e; thus, it is unknown what parameter estimates might have been before Wechsler et al. began adding cross-loadings and correlated errors seemingly for model improvement. There was also no report of CFA for the model implied by the subtest creation, descriptions, and assignments to the five factors presented in the WAIS–5 Technical Manual (see pp. 9-15). Despite claiming Arithmetic is a measure of FR in the WAIS–5, Wechsler et al. began CFA with Arithmetic assigned to WM along with the other seven WM subtests. In later models, subtest cross-loadings were sequentially added ("allowed"): Arithmetic (WM & FR; Model 5b), Symbol Span (WM & VS; Model 5c), Spatial Addition (WM & VS; Model 5d). Finally, Wechsler et al. added correlated errors for Running Digits and Digits Forward which completed construction of the final "optimal" model (see Figure 1).

Additional concerns relate to the continued absence of variance estimates for the factors representing various provided scores given the specified measurement model as previously called for in two Mental Measurements Yearbook reviews [Canivez, 2010; 2014] and a review of the WISC–V [Canivez & Watkins, 2016]). Model-based reliability and dimensionality estimates were also not provided which would help users determine how well various scores might be indexed to guide whether or not scores provided convey sufficient true score measurement for clinical use. Reise et al. (2023) emphasized,

> In the development of new measures or the psychometric analysis of existing measures, there is no defensible reason for failing to report indices such as ω, ω_H, ω_{HS}, and ECV; if the data are consistent with a correlated factors model, they will also, in general, be consistent with a bifactor model[7]; those statistics are important to report so that researchers can judge whether the subscales provide any unique and reliable information once controlling for the general (p. 343).

Purpose

The WAIS–5 Technical Manual (Wechsler et al., 2024) lacks sufficient and necessary information regarding structural validity evidence which is surprising given that understanding the structural validity of tests is crucial for evaluating interpretability of provided scores (AERA et al., 2014). Revised tests should be treated like a new test when considering structural validity because it cannot be assumed that scores from the revision would be directly comparable to the previous version without appropriate supporting evidence (Beaujean, 2015). This certainly applies to the WAIS–5 with the addition of five new subtests, removal of two subtests, change in item content, new administrative and scoring procedures, and obtaining a new normative sample. Given the absence of EFA, inadequately described and presented CFA, absence of assessment of plausible rival models (no examination of models with fewer than 5 group factors and no consideration of bifactor structure), and lack of inclusion of model-based reliability/validity and dimensionality estimates in the WAIS–5 Technical Manual; the present study (a) used EFA best practices (Watkins, 2018) to assess the WAIS–5 factor structure suggested by the 20 primary and secondary subtest relationships, (b) assessed the WAIS–5 factor structure using CFA including models ignored by Wechsler et al., (c) compared bifactor models to higher-order models as alternate explanations, (d) decomposed EFA and CFA factor variance sources to understand true-score variance contributions, and (e) examined WAIS–5 model-based reliability/validity and dimensionality (Watkins, 2017, 2021) of plausible models. It is believed that the results of these analyses will help to provide insight on the interpretive value of the panoply of scores and score comparisons provided in the WAIS–5 and interpretive guidelines promulgated by the publisher. Widespread adoption and use of the instrument immediately after its publication illustrate the importance of these results for advancing evidence-based assessment in clinical practice.

Method

Participants

The full WAIS–5 standardization sample (*N* = 2,020) ranged in age from 16-90 years and included 13 age groups. Details of sampling and normative sample information is available in the WAIS–5 Technical Manual and stratification variables included sex, education level, race/ethnicity, and geographic region. The normative sample closely matched the 2022 U.S. census estimates for these key demographic variables. Institutional Review Board review obtained by the first author confirmed it was exempt given secondary analysis of statistical summary data published in the WAIS–5 Technical Manual (Wechsler et al., 2024).

Instrument

The WAIS–5 (Wechsler, 2024) is a general intelligence test composed of 20 subtests indexed with scaled scores (*M* = 10, *SD* = 3). There are ten primary subtests (Similarities [SI], Vocabulary [VC], Block Design [BD], Visual Puzzles [VP], Matrix Reasoning [MR], Figure Weights [FW], Digit Sequencing [DSQ], Running Digits [RD], Coding [CD], Symbol Search [SS]) used to measure five factor-based Primary Index scales (composite scores): Verbal Comprehension Index (VCI), Visual-Spatial Index (VSI), Fluid Reasoning Index (FRI), Working Memory Index (WMI), and Processing Speed Index (PSI). Seven of the primary subtests (SI, VC, BD, MR, FW, DSQ, CD) are used to produce the FSIQ. Secondary subtests (Information [IN], Comprehension [CO], Arithmetic [AR], Set Relations [SR], Digits Forward [DF], Digits Backward [DB], Letter-Number Sequencing [LN], Naming Speed Quantity [NSQ], Symbol Span [SSP], Spatial Addition [SA]) are used to produce Ancillary Index scales (5 Expanded Index Scores, 6 Domain-Specific Index Scores, 4 Summary Index Scores). However, ancillary scores do not contribute to the measurement of intelligence and thus were not the focus of the present investigation. Index scores and the FSIQ are scaled as standard score metrics (*M* = 100, *SD* = 15).

Analyses

Independent EFA and CFA were conducted using the full WAIS–5 standardization sample (*N* = 2,020) summary statistics (subtest correlations, means, and standard deviations) provided in the WAIS–5 Technical Manual (Wechsler et al., 2024, Table 5.1, p. 74). While the correlations were rounded to only two decimals this level of precision was deemed sufficient (Carroll, 1993) and has been frequently used in other studies (i.e., Canivez et al., 2016, 2017).

Exploratory Factor Analyses (EFA). EFA was used to “allow data to speak for themselves” (Carroll, 1995, p. 436) and to provide evidence that might support plausible models to later test in CFA to accord with factor analytic best practice (Carroll, 1995; Reise, 2012). The 20 WAIS–5 primary and secondary subtest correlation matrix was used to conduct EFAs with SPSS 29 for Macintosh. Multiple criteria were examined and compared for their suggestion of the number of factors that might be extracted and retained (Gorsuch, 1983), including eigenvalues > 1 (Kaiser, 1960), the scree test (Cattell, 1966), standard error of scree (SE_{scree}; Zoski & Jurs, 1996), parallel analysis (PA; Horn, 1965), Glorfeld’s (1995) modified PA (see Figure 2), minimum average partials (MAP, Velicer, 1976; Frazier & Youngstrom, 2007), and exploratory graph analysis (Golino et al., 2022). EFA was conducted using IBM SPSS 29 for Macintosh (IBM, 2024) and additional software where noted. The SE_{scree} program (Watkins, 2007) was used as Nasser et al. (2002) indicated SE_{scree} was the most accurate objective scree method. Random data and resulting eigenvalues for PA using both mean and 95% confidence intervals (Glorfeld, 1995) were produced using SPSS syntax (O’Connor, 2000) with 100 replications to provide stable eigenvalue estimates. PA was not the only criterion as Crawford et al. (2010) reported that PA frequently suggests retaining too few factors (underextraction) in the presence of a strong general factor. MAP was also examined using the O'Connor (2000) SPSS syntax. Exploratory graph analysis (i.e., network) was conducted using **R** and the *EGAnet* package (Golino et al., 2022) as a newer method for suggesting the number of latent dimensions.

Principal axis extraction of factors was followed by oblique rotation with promax ($k = 4$; Gorsuch, 1983). Viable factors required a minimum of two subtests with salient factor pattern coefficients (≥ .30; Child, 2006). Because the WAIS–5 explicitly adopted a higher-order structure, the Schmid and Leiman transformation (SLT; Schmid & Leiman, 1957) procedure was applied to disentangle the variance contributions of first and second order factors, as advocated by Carroll (1993, 1995, 2003) and Gignac (2005). The SLT has been used in numerous EFA studies including with the WISC–V (Canivez et al., 2016; Canivez et al., 2018; Canivez et al., 2020; Dombrowski et al., 2018). The SLT decomposes each subtest score variance into general factor variance first and then first-order factor variance. The first-order factors are modeled orthogonally to each other and to the general factor (Gignac, 2006; Gorsuch, 1983). The SLT was produced using the *MacOrtho* program (Watkins, 2004) and disentangles the common variance explained by the general factor and the residual common variance explained by the first-order factors.

Confirmatory Factor Analyses (CFA). Confirmatory factor analysis (CFA) with maximum likelihood estimation was conducted using *Mplus* 8.6 for Macintosh (Muthén & Muthén, 2021). Covariance matrices were reproduced for CFA using the 20 subtest correlation matrix, means, and standard deviations obtained from the WAIS–5 standardization sample reported in Table 5.1 (Wechsler et al., 2024). As with other similar studies (e.g., Canivez, Watkins, & Dombrowski, 2017; Watkins, Dombrowski, & Canivez, 2018) identification of latent variable scales set a reference indicator to 1.0 in higher-order models and setting the variance of latent variables to 1.0 in bifactor models (Brown, 2015; Byrne, 2006). As with other Wechsler scales (i.e., U.S. and international WISC–V versions), the VS factor is underidentified in several models because it contains only two subtest indicators (Block Design and Visual Puzzles). Thus, in specifying the VS factor with only two indicators in CFA bifactor models, the two subtests' group factor path coefficients were constrained to equality prior to estimation to ensure identification (Little et al., 1999).

Alternate structural models implied by Wechsler scale historical antecedents (i.e., Wechsler, 2003) and the WAIS–5 subtest creation and assignments are presented in Figures 2 and 3 and were examined via CFA. Models designated with "h" are higher-order models, those designated with "b" are bifactor representations, and models without the "h" or "b" are oblique models. Model 1 includes all 20 subtests on a single general intelligence factor similar to Wechsler (2008), Model 2A distinguishes the four Verbal Comprehension subtests on one factor and all other subtests on a second, while Model 2B placed subtests associated with verbal reasoning on one factor and subtests associated with nonverbal reasoning on a second factor similar to WAIS–IV Model 2 (Wechsler, 2008). Subtest assignments for Model 3 and 3h are identical to WAIS–IV Model 3 with Verbal Comprehension subtests on Factor 1, Visual Spatial and Fluid Reasoning subtests on Factor 2 (i.e., Perceptual Reasoning), and Working Memory and Processing Speed subtests on Factor 3 as on the WAIS–IV (Wechsler, 2008). Subtest assignments for Models 4, $4h_1$, and $4b_1$ are based on subtest creation and assignment specified by Wechsler et al. (2024, pp. 9-15) with Verbal Comprehension subtests on Factor 1, Visual Spatial and Fluid Reasoning collapsed into a Perceptual Reasoning factor (like the WAIS–IV) on Factor 2, Working Memory subtests on Factor 3, and Processing Speed subtests on Factor 4. Models $4h_2$

and $4b_2$ are identical to the previous four factor models but placed Arithmetic on the Working Memory factor. Models $4h_3$ and $4b_3$ then moved Symbol Span and Spatial Addition subtests to the Perceptual Reasoning factor (still collapsing Visual Spatial and Fluid Reasoning subtests). Finally, subtest assignments for CFA models with five factors are illustrated in Figure 3. Models 5, $5h_1$, and $5b_1$ are models based on subtest assignments to the five factors described by Wechsler et al. (2024, pp. 9-15) with the four Verbal Comprehension subtests, two Visual Spatial subtests, four Fluid Reasoning subtests (including Arithmetic), seven Working Memory subtests, and three Processing Speed subtests; but which were *not* included or reported in the Wechsler et al. CFA. Models $5h_2$ and $5b_2$ are the same and the previous model but moving Arithmetic to Working Memory while Models 5h3 and 5b3 moved Arithmetic to Working Memory and moved Symbol Span and Spatial Addition to the Visual Spatial factor. Unlike Wechsler et al. (2024) models 5b through 5e, the present study *did not* include cross-loadings or correlated errors (residuals) in a search for better global model fit, which likely masks model problems and increases model complexity. Such practices have long been criticized in the methodological literature (Landis et al., 2009; MacCallum et al., 1992).

Although approximate fit indices have no universally accepted cutoff values (McDonald, 2010), overall global model fit was evaluated using the comparative fit index (CFI), standardized root mean squared residual (SRMR), and the root mean square error of approximation (RMSEA). Higher CFI values indicate better fit whereas lower SRMR and RMSEA values indicate better fit. Hu and Bentler (1999) combinatorial heuristics suggest *adequate* model fit with CFI $\geq .90$ along with SRMR $\leq .09$ and RMSEA $\leq .08$. *Good* model fit required CFI ≥ 0.95 with SRMR and RMSEA ≤ 0.06 (Hu & Bentler, 1999). Additionally, the Akaike Information Criterion (AIC) was reported but because it does not have a meaningful scale, the model with the smallest AIC value was preferred (Kline, 2016). Superior model fit required adequate to good overall fit *and* display of meaningfully better fit using ΔCFI > .01 and ΔRMSEA > .015 (F. F. Chen, 2007; Cheung & Rensvold, 2002) and ΔAIC > 10 (Burnham & Anderson, 2004) criteria. McDonald and Ho (2002) noted that global fit indexes may mask local misfit that might invalidate models so in addition to assessing global fit, standardized parameter estimates within each model were examined as indicators of local fit to make sure they made statistical and substantive sense (Brown, 2015) because models should never be retained "solely on global fit testing" (Kline, 2016, p. 461).

In both EFA and CFA, model-based reliability/validity was estimated with coefficients omega-hierarchical (ω_H) for the general factor and omega-hierarchical subscale (ω_{HS}) for group (first-order) factors, which estimate reliability of *unit-weighted* scores produced by the specified indicators (Reise, 2012; Rodriguez et al., 2016a, 2016b). ω_H is the model-based reliability estimate for the general intelligence factor with variability of group factors removed. ω_{HS} is the model-based reliability estimate of a group factor with all other group *and* general factors removed (Brunner et al., 2012; Reise, 2012) and thus an indicator of unique measurement contribution of the group factor. Omega estimates (ω_H and ω_{HS}) may be obtained for SLT decomposed variance estimates from EFA and CFA higher-order models as well as from CFA bifactor solutions and were produced using the *Omega* program (Watkins, 2013), which is based on the tutorial by Brunner et al. (2012) and the work of Zinbarg et al. (2005) and Zinbarg et al. (2006). Omega coefficients of .75 are preferred, but should at a minimum exceed .50 (Reise, 2012; Reise et al., 2013).

The *H* coefficient (Hancock & Mueller, 2001) is a construct reliability or construct replicability coefficient and the correlation between a factor and an *optimally weighted* composite score and was used to supplement omega coefficients. *H* represents how well the latent factor is represented by the specified indicators and was produced using the *Omega* program (Watkins, 2013) and a criterion value of .70 (Hancock & Mueller, 2001; Rodriguez et al., 2016a, 2016b) was applied. Model-based dimensionality estimates (percentage of uncontaminated correlations [PUC] and explained common variance [EVC]) were also examined as produced in the *Omega* (Watkins, 2013) program (see also Watkins & Canivez, 2022).

Results

Exploratory Factor Analyses

The correlation matrix was judged acceptable for factor analysis with the Kaiser-Meyer-Olkin Measure of Sampling Adequacy of .961 that far exceeded the .60 minimum standard (Kaiser, 1974; Tabachnick & Fidell, 2007) and Bartlett's Test of Sphericity (Bartlett, 1954), $\chi^2 = 21{,}593.01$, $p < .0001$; indicated that the WAIS–5 correlation matrix was not random. Without standardization sample raw data, it was not possible to estimate univariate subtest skewness and kurtosis or multivariate normality; however, principal axis extraction does not require normality.

Figure 1A in the online Appendix illustrates the scree plots from PA for the WAIS–5 total standardization sample. Visually examined scree suggested one factor while MAP suggested two. Eigenvalues > 1 and PA suggested three factors while the SE_{scree} suggested four factors. Exploratory graph analysis (Golino et al., 2022) results are presented in Figure 2A in the online Appendix and also suggested four factors. The publisher purported theory reflects five latent factors. Thus, EFA began by extracting five factors to examine subtest associations based on the publisher's desired and promoted structure and to allow examination of the performance of smaller factors because Wood et al. (1996) noted that it is better to overextract than underextract. Models with four, three, and two factors were subsequently examined for adequacy.

Five Factor Extraction. Results of five-factor extraction with subsequent promax rotation presented in Table 1 illustrates that all subtests (except RD and NSQ) demonstrated fair to good *g* loadings (subtest structure coefficients with the first unrotated factor) according to Kaufman's (1994) criteria and ranged from .453 (NSQ) to .755 (FW). Separate Visual Spatial and Fluid Reasoning factors *did not* emerge as BD, VP, MR, FW, and SR subtests all had salient factor pattern coefficients on the same factor (Factor 1: Perceptual Reasoning [PR]). The SSP and SA subtests also had salient factor pattern coefficients on this PR factor (suggested also by EGA) and *did not* have salient factor pattern coefficients on the WM factor which they were constructed to measure (Wechsler et al., 2024). Factor 2: Verbal Comprehension (VC) contained the traditional subtest content (SI, VC, IN, CO). Factor 3: Working Memory (WM) included most of the expected subtests (RD, DF, DB, LN) created to measure working memory, but DSQ, SSP, and SA *did not* have salient pattern coefficients on WM. CD, SS, and NSQ had salient pattern coefficients on Factor 4: Processing Speed (PS). Factor 5 contained two subtests with singular salient factor pattern coefficients (AR, DSQ), while two subtests had small but salient cross-loadings (DB, SA). These psychometrically unsatisfactory results are emblematic of overextraction (Gorsuch, 1983; Wood et al., 1996) and the five-factor model was thus judged inadequate.

Four Factor Extraction. Table 2 presents the results of extracting four factors with subsequent promax rotation. Factor 1: Perceptual Reasoning (PR) included salient pattern coefficients for all subtests purported to measure Visual Spatial (BD, VP) *and* Fluid Reasoning (MR, FW, AR, SR), further illustrating merging of VS and FR factors into one complexly determined dimension. Salient pattern coefficients on the PR factor were also observed for SSP and SA subtests that were supposed to be indicators of WM (Wechsler et al., 2024). Thus, VS and FR do not appear to be separately captured by WAIS–5 subtests. Factor 2: Verbal Comprehension (VC) included salient factor pattern coefficients for SI, VC, IN, and CO subtests. Factor 3: Working Memory included salient pattern coefficients for DSQ, RD, DF, DB, and LN subtests. AR also had a salient cross-loading on WM. SSP and SA, two subtests designed and selected as measures of WM *did not* have salient factor pattern coefficients on WM. Factor 4: Processing Speed (PS) included CD, SS, and NSQ subtests with salient factor pattern coefficients. Of the 20 WAIS–5 subtests, 19 singularly loaded on a factor and the only subtest to cross-load two factors was AR (PR and WM). The moderate to high factor correlations presented in Table 2 (.499 to .726) suggested the presence of a general intelligence factor (Gorsuch, 1983) requiring explication through second-order EFA and application of the SLT to decompose sources of variance.

Three and Two Factor Extraction. Table 1A in the online Appendix presents results from extractions of three factors and two factors and subsequent promax rotation. The two- and three-factor models clearly displayed fusion of potentially theoretically meaningful constructs and numerous subtests with cross-loadings that is symptomatic of underextraction, thereby rendering them unsatisfactory (Gorsuch, 1983; Wood et al., 1996).

Second-order EFA and SLT. Given that the four-factor EFA solution was the most plausible, it was subsequently subjected to second-order EFA and results transformed with the SLT procedure (see Table 3). Following SLT, residual loadings and variance of most WAIS–5 subtests were properly associated with their theoretically proposed factors (Wechsler model). AR had a slightly larger residual loading and variance with WM than PR and both SSP and SA residual loadings and variance were apportioned to PR and not WM. As would be expected from the fair to good *g* loadings of WAIS–5 subtests, most common subtest variance was apportioned to the general (*g*) factor and the hierarchical *g* factor accounted for 40.4% of the total variance and 72.0% of the common variance. The general factor also accounted for between 17.4% (NSQ) and 55.1% (FW) of individual subtest variability.

At the group factor level, PR accounted for an additional 2.5%, VC an additional 4.4%, WM an additional 4.5%, and PS an additional 4.2% of the total variance. Of the common variance, PR accounted for an additional 4.5%, VC an additional 7.9%, WM an additional 8.0%, and PS an additional 7.6%. The general and group factors combined to measure 56.1% of the total variance in WAIS–5 scores, leaving 43.9% unique variance (combination of specific and error variance).

Model-Based Reliability and Dimensionality. ω_H and ω_{HS} coefficients were estimated based on the SLT results and presented in Table 3, assigning AR to the WM factor due to its larger residual variance with WM. The ω_H coefficient for general intelligence (.877) was high and sufficient for scale interpretation of a unit-weighted composite score based on the indicators; however, the ω_{HS} coefficients for all four WAIS–5 group factors (PR, VC, WM, PS) were considerably lower (.102–.374), failing to meet the minimum value of .50. Thus, unit-weighted composite scores based on all subtest indicators of the four WAIS–5 group factors (PR, VC, WM, PS), possess too little unique true score variance for confident clinical interpretation (Reise, 2012; Reise et al., 2013). *H* indexes indicated an optimally weighted composite score for *g* accounted for 93.5% of *g* variance, but each of the group factors (PR, VC, WM, PS) were not adequately defined by their optimally weighted indicators (*H*s < .70). The PUC and ECV estimates for the *g* factor suggests essential unidimensionality. Figure 3 provides a visualization of variance sources of WAIS–5 subtests and composite scores based on the SLT orthogonalization of the EFA higher-order model.

Confirmatory Factor Analyses

Global Fit. CFA results for the 20 WAIS–5 primary and secondary subtests are presented in Table 4. Fit heuristics proposed by Hu and Bentler (1999) indicated that Models 1 (*g*), 2A, and 2B were inadequate as evidenced by too low CFI and RMSEA estimates that were too high (Models 1 & 2B). Models 3 and 3h demonstrated adequate fit; however, all higher-order and bifactor models that included four or five group factors produced superior global fit statistics with most achieving good model fit to these data–better than one-, two-, or three-factor models. Bifactor representations with four and five group factors produced superior CFI and AIC estimates than corresponding higher-order representations with the same subtest configurations (see Figures 3 & 4); however, meaningful differences in RMSEA were observed only for Models $4b_2$ and $4b_1$. The best fitting model was Model $4b_3$ (see Figure 5) which is the similar to the SLT EFA model with four group factors. Although Model $4b_3$ was better than $4h_3$, Model $4h_3$ was well fitting and is also presented in detail below (see Figure 6). All bifactor models were superior to corresponding higher-order versions (ΔAIC > 10). It is worth noting that the model implied based on WAIS–5 subtest construction and assignment described by Wechsler et al. (2024, pp. 9-15), but which was *not* examined in their CFA, *was* examined in the present study (Model $5h_1$). As noted in Table 4, this model produced an improper solution with a latent variable covariance matrix that was not positive definite and a standardized path coefficient from *g*–FR = 1.004 that was out of bounds (See Online Appendix Figure 11A).

Local Fit and Parameter Estimate Problems. While all permissible models with four or five group factors achieved adequate or good *global fit*, assessment of local fit and parameter estimates identified numerous problems. Table 5 summarizes each of the models' local fit and parameter estimate problems (i.e., non-statistically significant standardized path coefficients, negative standardized path coefficients, standardized path coefficients ≥ 1.0, small standardized path coefficients [< .30], very high second-order standardized path coefficients [> .90]). As a result, most of these models were considered inadequate. For complete reporting, each of the bifactor and higher-order models with four and five group (first-order) factors not further reported here are presented in the Online Appendix and include their standardized measurement model, decomposed variance estimates, model-based reliability/validity and dimensionality estimates, and variance visualizations.

Model Selection. According to the CFI, SRMR, RMESA, and AIC criteria, Model $4b_3$ (see Figure 5) was the best fit and it also exceeded all other models according to the ΔAIC > 10 criterion. Model $4b_3$ also had the fewest local fit or parameter estimate problems (see Table 5). Of the higher-order models, Model $4h_3$ (see Figure 6) achieved best fit and had fewer local fit or parameter estimate problems compared to other higher-order models (see Table 5).

Variance, Reliability, & Dimensionality: Model $4b_3$. Table 6 presents sources of variance for Model $4b_3$ and illustrates that for most subtests, larger portions of variance was associated with general intelligence. The exceptions were Running Digits, Coding, and Naming Speed Quantity. Visualization of WAIS–5 subtest and composite score variance sources for Model $4b_3$ is presented in Figure 7 and illustrates the dominance of *g*. ω_H and ω_{HS} coefficients in Table 6 show the ω_H coefficient for general intelligence (.887) was high and sufficient for confident scale interpretation of a unit-weighted score based on its indicators. The ω_{HS} coefficients for the four WAIS–5 group factors (VC, PR, WM, PS), however, were considerably lower, ranging from .069 (PR) to .361 (PS), indicating they possess too little unique true score variance in a unit-weighted composite score to support confident clinical interpretation (Reise, 2012; Reise et al., 2013). *H* indexes indicated an optimally weighted composite score for *g* accounted for 93.9% of *g* variance, but the four group factors were not well defined by their optimally weighted indicators (*H*s < .70). Further, with PUC = .763 and ECV = .736, the general dimension might be considered essentially unidimensional (Gu et al., 2017; Rodriguez et al., 2016a, 2016b; Sellbom & Tellegen, 2019).

Variance, Reliability, & Dimensionality: Model $4h_3$. For comparison purposes, Table 7 presents sources of variance for Model $4h_3$ and illustrates that all subtests had larger portions of variance apportioned to general intelligence. Visualization of WAIS–5 subtest and composite score variance sources for Model $4h_3$ is presented in Figure 8. ω_H and ω_{HS} coefficients in Table 7 show the ω_H coefficient for general intelligence (.888), like Model $4b_3$, was high and sufficient for confident scale interpretation of a unit-weighted score based on its indicators. The ω_{HS} coefficients for the four WAIS–5 group factors (VC, PR, WM, PS), like Model $4b_3$, however, were considerably lower, ranging from .082 (PR) to .370 (PS), indicating they possess too little unique true score variance in a unit-weighted composite score to support confident clinical interpretation (Reise, 2012; Reise et al., 2013). *H* indexes indicated an optimally weighted composite score for *g* accounted for 93.8% of *g* variance, but the four group factors were inadequately defined by their optimally weighted indicators (*H*s < .70). Like Model $4b_3$, with PUC = .763 and ECV = .766, the general dimension might be considered essentially unidimensional (Gu et al., 2017; Rodriguez et al., 2016a, 2016b; Sellbom & Tellegen, 2019).

Discussion

Results from the present independent EFA and CFA with the 20 WAIS–5 primary and secondary subtests substantially challenge the purported structure promoted by Wechsler et al.

(2024) in the WAIS–5 Technical Manual. None of the quantitatively based EFA extraction criteria supported five latent factors underlying the 20 WAIS–5 subtest correlation matrix, results also observed with the WISC–V (Canivez et al., 2016; Canivez et al., 2018; Canivez & Watkins, 2016; Dombrowski et al., 2021). Even when forcing extraction of five factors to accord with publisher theory, a viable fifth factor did not emerge. Specifically, the fifth factor included only two unique subtest loadings (Arithmetic, Digit Sequencing) but also had two smaller subtest cross-loadings (Digits Backward, Spatial Addition) which is indicative of overfactoring and thus judged inadequate. Subtests intended to separately measure VS and FR factors, even when five factors were extracted, saliently loaded on the same factor which resembled the former WAIS–IV Perceptual Reasoning (PR) dimension, results also found with the WISC–V (Canivez et al., 2016; Canivez et al., 2018; Canivez & Watkins, 2016; Dombrowski et al., 2021). Given the complexly determined factor represented by subtests purporting to measure VS and FR, the name Perceptual Reasoning seems more appropriate, although it is crucial that both the *naming fallacy* and *reification* be avoided (Kline, 2011). What is clear from the present EFA results is that separate VS and FR dimensions were not supported as implied via publisher theory.

CFA results in the present study found the best representation of WAIS–5 latent structure was a bifactor model with four group factors (Model $4b_3$), which was consistent with the four factor EFA model with SLT, but while it was judged "best" it contained several problematic standardized path coefficients from group factors to subtests that were either not statistically significant or low. In contrast, the *g* factor had statistically significant coefficients with all subtests. While two bifactor models with five group factors (Model $5b_1$ and Model $5b_2$) had global fit indexes that were not meaningfully different from the Model $4b_3$, there were standardized factor path coefficients that were not statistically significant, rendering the FR group factor implausible (see Figures 12A and 16A in online Appendix). Other models with five group factors in both higher-order and bifactor representations resulted in more local fit and parameter estimation problems or model misspecification, rendering them implausible (see Table 5).

Similar problems might also have been present in the higher-order models examined by Wechsler et al. (2024) but without disclosure of standardized path coefficients in their measurement models except for the "optimal" Model 5e, it is not possible to fully assess them or whether adding subtest cross-loadings and correlated errors were attempts to correct local model misfit or parameter estimate problems. Based on the subtest creation and assignment described in the WAIS–5 Technical Manual by Wechsler et al. (pp. 9-15), the implied measurement model (see Figure 4 for subtest assignments) was inexplicably not tested and reported. This model was examined in the present study (Model $5h_1$) but resulted in the latent variable covariance matrix that was not positive definite and produced a Heywood case (*g*–FR path coefficient of 1.004 and negative residual variance estimate) that rendered this model impermissible. Similar problems were identified in WISC–V CFA when specifying five group factors (Canivez et al., 2017; Canivez & Watkins, 2016; Wechsler, 2014) and may be the result of overfactoring. If this same estimation problem was encountered during WAIS–5 validation, it was not reported or disclosed.

In both EFA and CFA, resulting models were further assessed using model-based reliability and dimensionality estimates to determine viability of factor based scores based on subtest indicators. In the EFA based SLT of the second-order solution, CFA based bifactor models, and CFA based higher-order models with SLT; all showed substantial subtest variance associated with the *g* factor resulting in ω_H coefficients exceeding preferred levels for unit-weighted scores and *H* coefficients also exceeding preferred levels for optimally weighted scores. Thus, regardless of model, composite scores representing the *g* factor would be well defined. In all EFA and CFA models, none of the first-order group factors had ω_{HS} coefficients meeting the minimum levels for unit-weighted scores and none had *H* coefficients meeting minimum standards for optimally weighted composite scores. Thus, none of the first-order group factors appear to have sufficient unique variance remaining after *g* variance was removed and thus would not be well defined for confident clinical interpretation. Finally, dimensionality of EFA and CFA based models was assessed with PUC and ECV and it appeared that the *g* factor of the WAIS–5 was essentially unidimensional. Similar results appeared with the WISC–V (Canivez et al, 2016, 2017; Canivez & Watkins, 2016;) and WAIS–IV (see Nelson et al., 2013).

Structurally, the WAIS–5 appears to be an excellent measure of *g,* but little else, and thus interpretation of the FSIQ or GAI as an estimate of general intelligence is strongly supported. As constructed, WAIS–5 factor index scores, like those in all other Wechsler scales (WISC–V, WPPSI–IV), conflate true score variance due to *g* and true score variance due to the construct it purports to measure, so, for example, the VCI is not an index of verbal abilities per se but the VCI is a mixture of general intelligence variance *and* some amount of unique verbal comprehension variance and thus not a univocal score. Therefore, broad interpretation of WAIS–5 factor index scores is not supported based on present results and requires additional examination of reliability and validity methods (i.e., longitudinal stability, incremental predictive validity, diagnostic utility) to determine specific conditions where such interpretation *might be* empirically supported.

Limitations

As with all studies, there are notable limitations in the present investigation. One limitation is that present analyses were conducted using correlation matrices and descriptive statistics from the WAIS–5 Technical Manual (Wechsler et al., 2024) so it was not possible to examine structural validity or factorial invariance across variables such as sex, race/ethnicity, or socioeconomic status. Wechsler et al. did not report factor invariance across demographic subgroups within the normative sample so such examinations will require the publisher to share standardization sample data with independent scholars if not furnishing those internal results, when or if conducted. Also, because these analyses were conducted with summary statistics from the normative sample, replication should be conducted with clinical groups for which the WAIS–5 is likely to be used and with independent samples of non-clinical groups, participants of different races/ethnicities, nationalities, and language minorities to judge the adequacy of future WAIS–5 adaptations.

While the present study assessed WAIS–5 structural validity, other validity studies also need to be conducted such as incremental predictive validity to assess how well the factor index scores predict meaningful outcomes such as academic achievement after controlling for the FSIQ (Glutting et al., 2006). While Wechsler et al. had data that would have permitted such incremental validity examinations with the standardization sample who were also given the WIAT–4 ($N = 204$), only zero-order Pearson correlations between scores from these instruments were provided in the WAIS–5 Technical Manual so it is unknown how much of the factor index score correlations with measures of academic achievement were due to the conflated *g* variance within them. Canivez (2013) and Nelson et al. (2013) showed how the WAIS–IV FSIQ accounted for large portions of achievement variance while the WAIS–IV factor index scores often contributed only trivial to small incremental prediction beyond the FSIQ. Kranzler and Floyd (2015) found similar results in their latent variable approach although VC contributed some additional important explanations for some achievement domains (Word Reading, Reading

Comprehension, Spelling, and Listening Comprehension subtests; Reading, Oral Language, and Total Achievement composite scores).

Finally, although the WAIS–5 offers a wide array of ancillary scores for clinical interpretation, it remains unclear whether these scores reflect viable psychological dimensions or are merely pseudo composites to enhance the instrument's marketability (Dombrowski et al., 2022; Frazier & Youngstrom, 2007) or "cash validity" (Kush et al., 2011). None of the ancillary scores were featured in any meaningful way in the structural analyses reported in the WAIS–5 Technical Manual and thus their relationships with WAIS–5 primary dimensions are unknown. Previous analyses of the structural validity of similar scores on the WISC–V did not support the retention of those dimensions within a broader Wechsler interpretive framework (McGill et al., 2025).

Conclusion

Based on the present results, the WAIS–5 as presented by Wechsler et al. (2024) appears to be overfactored and the overwhelming dominance of general intelligence variance identified within indicates primary, if not exclusive, interpretive focus on the FSIQ. As with the WISC–V, the attempt to split the PR factor into separate VS and FR factors was unsuccessful as there was no viable FR factor located, as posited, by this investigation. Thus, FR standard scores and comparisons may be misleading and users will likely overinterpret or misinterpret FR scores. The present results provide users of the WAIS–5 crucial information so they may make informed decisions about whether, when, and how to use the WAIS–5 and which scores have sufficient psychometric support for confident interpretation and psychodiagnostic inferences. Statistical analyses and results presented in the present study show why researchers and clinicians must rely on more than the test technical manual to appropriately use test scores and their comparisons.

Present results will help professionals ethically use the WAIS–5 as they must "know what their tests can do and act accordingly” (Weiner, 1989, p. 829), because test users bear “the ultimate responsibility for appropriate test use and interpretation” (American Educational Research Association, American Psychological Association, & National Council on Measurement in Education, 2014, p. 141).

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Table 1

Wechsler Adult Intelligence Scale-Fifth Edition (WAIS–5) Exploratory Factor Analysis: Five Oblique Factor Solution for the Total Standardization Sample (N = 2,020)

	General	F1: Perceptual Reasoning		F2: Verbal Comprehension		F3: Working Memory		F4: Processing Speed		F5: Inadequate		
WAIS–5 Subtest	*S*	*P*	*S*	*P*	*S*	*P*	*S*	*P*	*S*	*P*	*S*	h^2
Similarities	.702	.163	.632	**.664**	.766	.018	.480	.034	.424	-.072	.493	.599
Vocabulary	.728	-.046	.608	**.888**	.860	.061	.533	.006	.403	-.054	.517	.742
Information	.700	.017	.601	**.767**	.797	-.016	.490	-.025	.384	.064	.531	.638
Comprehension	.708	.043	.615	**.763**	.799	-.036	.476	.041	.425	.009	.517	.641
Block Design	.696	**.729**	.742	.054	.561	.038	.437	.124	.525	-.178	.476	.567
Visual Puzzles	.716	**.854**	.783	.004	.572	.033	.458	-.040	.460	-.096	.518	.617
Matrix Reasoning	.711	**.729**	.753	.030	.573	.017	.470	-.048	.452	.031	.556	.570
Figure Weights	.755	**.678**	.786	.073	.617	-.079	.478	-.054	.480	.188	.633	.634
Arithmetic	.752	.297	.698	.134	.627	.078	.595	-.036	.476	**.389**	.721	.602
Set Relations	.680	**.514**	.685	.246	.617	-.018	.444	-.040	.415	.037	.523	.499
Digit Sequencing	.672	.100	.593	-.037	.493	.074	.571	.078	.500	**.596**	.742	.564
Running Digits	.470	.138	.390	.009	.386	**.690**	.625	-.072	.245	-.168	.384	.406
Digits Forward	.588	-.167	.424	.027	.467	**.812**	.807	.050	.381	.079	.580	.661
Digits Backward	.657	.129	.564	-.051	.494	**.440**	.695	-.010	.425	**.302**†	.668	.550
Symbol Span	.648	**.555**	.665	-.058	.482	.038	.452	.067	.477	.123	.549	.458
Spatial Addition	.702	**.416**	.690	-.033	.517	-.055	.472	.184	.578	**.301**†	.645	.545
Letter-Number Sequencing	.695	.130	.605	.080	.560	**.304**	.652	.068	.485	.270	.667	.534
Coding	.604	.008	.530	.023	.410	.004	.383	**.875**	.854	-.068	.457	.731
Symbol Search	.609	.168	.564	-.053	.406	.018	.401	**.665**	.758	.006	.488	.587
Naming Speed Quantity	.453	-.156	.365	.077	.332	-.033	.322	**.492**	.555	.243	.438	.337
Eigenvalue		9.31		1.36		1.25		.98		.70		
% Variance		44.50		4.88		4.09		2.83		1.11		
<u>Promax Based Factor Correlations</u>		F1: PR		F2: VC		F3: WM		F4: PS		F5		
Perceptual Reasoning (PR)		–										
Verbal Comprehension (VC)		.735		–								
Working Memory (WM)		.597		.603		–						
Processing Speed (PS)		.630		.482		.467		–				
F5		.716		.627		.709		.574		–		

Note. *S* = Structure Coefficient, *P* = Pattern Coefficient, h^2 = Communality. General structure coefficients are based on the first unrotated factor coefficients (*g* loadings) and those meeting Kaufman's (1994) criterion for "good" (≥ .70) are highlighted in dark shading while those meeting the "fair" criterion (.50-.69) are highlighted in light shading. Salient pattern coefficients presented in bold (pattern coefficient ≥ .30). †Small cross-loading.

Table 2

Wechsler Adult Intelligence Scale-Fifth Edition (WAIS–5) Exploratory Factor Analysis: Four Oblique Factor Solution for the Total Standardization Sample (N = 2,020)

	General	F1: Perceptual Reasoning		F2: Verbal Comprehension		F3: Working Memory		F4: Processing Speed		
WAIS–5 Subtest	*S*	*P*	*S*	*P*	*S*	*P*	*S*	*P*	*S*	h^2
Similarities	.703	.155	.633	**.648**	.764	-.018	.512	.029	.449	.598
Vocabulary	.729	-.061	.614	**.864**	.861	.063	.561	.005	.431	.744
Information	.700	.060	.611	**.729**	.793	.046	.533	-.015	.416	.633
Comprehension	.708	.065	.622	**.734**	.797	-.016	.517	.051	.453	.640
Block Design	.694	**.674**	.725	.086	.554	-.115	.471	.101	.540	.537
Visual Puzzles	.715	**.844**	.769	.030	.564	-.075	.499	-.065	.487	.597
Matrix Reasoning	.711	**.779**	.753	.033	.561	-.009	.522	-.064	.482	.569
Figure Weights	.755	**.795**	.794	.057	.602	-.014	.553	-.048	.519	.633
Arithmetic	.750	**.440**	.723	.101	.607	**.300**†	.671	-.003	.525	.579
Set Relations	.681	**.565**	.687	.237	.609	-.023	.493	-.048	.445	.500
Digit Sequencing	.667	.298	.629	-.067	.470	**.403**	.652	.140	.546	.495
Running Digits	.467	.014	.394	.055	.379	**.596**	.573	-.116	.269	.337
Digits Forward	.587	-.241	.451	.046	.452	**.913**	.786	.025	.414	.640
Digits Backward	.658	.187	.592	-.064	.473	**.651**	.738	-.007	.468	.557
Symbol Span	.648	**.620**	.673	-.060	.468	.069	.508	.070	.506	.459
Spatial Addition	.701	**.538**	.708	-.052	.499	.078	.554	.222	.612	.534
Letter-Number Sequencing	.696	.191	.631	.064	.542	**.479**	.701	.083	.525	.534
Coding	.602	-.046	.538	.038	.399	-.088	.428	**.900**	.836	.705
Symbol Search	.610	.139	.572	-.040	.393	-.034	.451	**.708**	.763	.588
Naming Speed Quantity	.452	-.095	.387	.055	.318	.091	.380	**.550**	.566	.327
Eigenvalue		9.31		1.36		1.25		.98		
% Variance		46.57		6.81		6.25		4.88		
Promax Based Factor Correlations		F1: PR		F2: VC		F3: WM		F4: PS		
Perceptual Reasoning (PR)		–								
Verbal Comprehension (VC)		.726		–						
Working Memory (WM)		.703		.623		–				
Processing Speed (PS)		.687		.499		.583		–		

Note. S = Structure Coefficient, *P* = Pattern Coefficient, h^2 = Communality. General structure coefficients are based on the first unrotated factor coefficients (*g* loadings). Salient pattern coefficients presented in bold (pattern coefficient ≥ .30). †Small cross-loading.

Table 3

Sources of Variance in the Wechsler Adult Intelligence Scale–Fifth Edition (WAIS–5) 20 Subtests EFA According to a Schmid-Leiman Orthogonalized Higher-Order Factor Model with Four First–Order (Group) Factors for the Total Standardization Sample (N = 2,020)

	General		Perceptual Reasoning		Verbal Comprehension		Working Memory		Processing Speed				
WAIS–5 Subtest	*b*	S^2	*b*	S^2	*b*	S^2	*b*	S^2	*b*	S^2	h^2	u^2	s^2
Similarities	.663	.440	.056	.003	**.398**	**.158**	-.012	.000	.020	.000	.602	.398	.248
Vocabulary	.676	.457	-.022	.000	**.531**	**.282**	.041	.002	.003	.000	.741	.259	.179
Information	.655	.429	.022	.000	**.448**	**.201**	.030	.001	-.010	.000	.631	.369	.279
Comprehension	.664	.441	.023	.001	**.451**	**.203**	-.010	.000	.036	.001	.646	.354	.254
Block Design	.681	.464	**.243**	**.059**	.053	.003	-.074	.005	.071	.005	.536	.464	.344
Visual Puzzles	.707	.500	**.304**	**.092**	.018	.000	-.049	.002	-.045	.002	.597	.403	.313
Matrix Reasoning	.700	.490	**.280**	**.078**	.020	.000	-.006	.000	-.045	.002	.571	.429	.329
Figure Weights	.742	.551	**.286**	**.082**	.035	.001	-.009	.000	-.034	.001	.635	.365	.285
Arithmetic	.717	.514	*.158*	*.025*	.062	.004	**.194**	**.038**	-.002	.000	.581	.419	.339
Set Relations	.662	.438	**.203**	**.041**	.146	.021	-.015	.000	-.034	.001	.502	.498	.438
Digit Sequencing	.632	.399	.107	.011	-.041	.002	**.261**	**.068**	.098	.010	.490	.510	.400
Running Digits	.428	.183	.005	.000	.034	.001	**.386**	**.149**	-.081	.007	.340	.660	.580
Digits Forward	.525	.276	-.087	.008	.028	.001	**.591**	**.349**	.017	.000	.634	.366	.246
Digits Backward	.615	.378	.067	.004	-.039	.002	**.422**	**.178**	-.005	.000	.562	.438	.348
Symbol Span	.634	.402	**.223**	**.050**	-.037	.001	.045	.002	.049	.002	.457	.543	.443
Spatial Addition	.679	.461	**.194**	**.038**	-.032	.001	.051	.003	.155	.024	.526	.474	.364
Letter-Number Sequencing	.653	.426	.069	.005	.039	.002	**.310**	**.096**	.058	.003	.532	.468	.328
Coding	.564	.318	-.017	.000	.023	.001	-.057	.003	**.629**	**.396**	.718	.282	.132
Symbol Search	.578	.334	.050	.003	-.025	.001	-.022	.000	**.495**	**.245**	.583	.417	.217
Naming Speed Quantity	.417	.174	-.034	.001	.030	.001	.059	.003	**.385**	**.148**	.328	.672	.462
Total Variance		.404		.025		.044		.045		.042	.561	.439	
ECV		.720		.045		.079		.080		.076			
ω		.950		.889		.882		.855		.773			
ω_H/ω_{HS}		.877		.102		.283		.230		.374			
Relative ω		.923		.115		.321		.269		.484			
Factor Correlation		.936		.320		.532		.479		.611			
H		.935		.321		.521		.534		.536			
PUC		.763											
FDI		.967		.567		.722		.731		.732			

Note. *b* = standardized loading of subtest on factor, S^2 = variance explained, h^2 = communality, u^2 = uniqueness, s^2 = subtest specificity (u^2 – error variance), ECV = explained common variance, ω = Omega, ω_H = Omega-hierarchical (general factor), ω_{HS} = Omega-hierarchical subscale (group factors), *H* = index of construct reliability, PUC = percentage of uncontaminated correlations, FDI = factor determinacy index. Bold type indicates largest coefficients and variance estimates consistent with the theoretically proposed factor. Italic type indicates alternate/cross-loading association. Light shaded cells indicate minimum standard met; dark shaded cells indicate preferred/desired standard met. Arithmetic placed with Working Memory for model-based reliability/validity and dimensionality estimates.

Table 4

Mplus 8.6 Maximum Likelihood CFA Fit Statistics for the 20 WAIS–5 Primary and Secondary Subtests for the Standardization Sample (N = 2,020)

Model	χ^2	*df*	CFI	SRMR	RMSEA	RMSEA 90% CI	AIC
1	3,534.7	170	.843	.058	.099	[.096, .102]	185,369
2A	2,355.0	169	.898	.049	.080	[.077, .083]	184,191
2B	3,096.6	169	.864	.055	.093	[.090, .095]	184,933
3 & 3h	1,921.9	167	.918	.044	.072	[.069, .075]	183,762
4	1,319.8	164	.946	.037	.059	[.056, .062]	183,166
$4h_1$	1,374.8	166	.944	.039	.060	[.057, .063]	183,217
$4b_1$	691.2	150	.975	.027	.042	[.039, .045]	182,565
$4h_2$	1,277.6	166	.948	.038	.058	[.055, .061]	183,119
$4b_2$	648.4	150	**.977**	**.026**	.041	[.037, .044]	182,522
$4h_3$	1,106.4	166	.956	.036	.053	[.050, .056]	182,948
$4b_3$	640.6	150	**.977**	**.026**	**.040**	[.037, .043]	**182,514**
5	1,225.0	160	.950	.036	.057	[.054, .060]	183,079
$5h_1$[1]			Improper solution, Model estimates not reported				
$5b_1$	795.1	151	.970	.029	.046	[.043, .049]	182,665
$5h_2$	1,297.4	165	.947	.039	.058	[.055, .061]	183,141
$5b_2$	722.3	151	.973	.028	.043	[.040, .046]	182,593
$5h_3$	1,138.1	165	.955	.037	.054	[.051, .057]	182,982
$5b_3$[2]			Improper solution, Model estimates not reported				

Note. CFI = Comparative Fit Index, SRMR = Standardized Root Mean Square Residual, RMSEA = Root Mean Square Error of Approximation, AIC = Akaike's Information Criterion. Model number indicates the number of group factors included in the model. Models specified by only the number are oblique, models with "h" specification are higher-order representations, and models with "b" specification are bifactor representations. In Models $5b_1$ and $5b_2$, Block Design and Visual Puzzles group factor loadings were constrained to equality to allow model estimation. Best fitting model coefficients are illustrated in bold. Indices not meaningfully different (ΔCFI < .01, ΔRMSEA < .015, ΔAIC $\leq$ 10) from best fit are shaded. Models with subscript 1 delineates models where Arithmetic was assigned to a factor (Perceptual Reasoning or Fluid Reasoning) other than Working Memory. Models with subscript 2 assigned Arithmetic to Working Memory. Models with subscript 3 assigned Arithmetic to Working Memory *and* assigned Symbol Span and Spatial Addition to Perceptual Reasoning (four factor models) or Visual Spatial (five factor models) rather than Working Memory. Subtest assignments to latent first-order factors are presented in Figures 2 and 3.

[1] Latent variable covariance matrix is not positive definite, standardized *g*–FR path coefficient = 1.004.

[2] Residual covariance matrix is not positive definite, Visual Puzzles negative residual variance estimate = -.155.

Table 5

CFA Global Fit, Local Fit, and Parameter Estimate Problems Identified Within Specified Models

Model	Global Fit, Local Fit, and Parameter Estimate Problems
1	Inadequate global model fit with low CFI and high RMSEA.
2A	Inadequate global model fit with high RMSEA.
2B	Inadequate global model fit with low CFI and high RMSEA.
3	Adequate global model fit, high factor correlations ($r_{\text{VR-PR}}$ = .813; $r_{\text{VR-WM}}$ =.740; $r_{\text{PR-WM}}$ =.888) imply a general dimension requiring explication.
3h	Adequate global model fit, standardized *g*–PR path coefficient (.988) was very high and indicated poor discriminant validity, PR indistinguishable from *g*.
4	Adequate global model fit, high factor correlations (.540-.888) imply a general dimension requiring explication.
$4h_1$	Adequate global model fit, standardized *g*–PR path coefficient (.965) and *g*–WM path coefficient (.925) were very high and indicated poor discriminant validity, PR indistinguishable from *g*; SLT standardized path coefficients for PR-Block Design, PR-Visual Puzzles, PR-Matrix Reasoning, PR-Figure Weights, PR-Arithmetic, PR-Set Relations, WM-Digit Sequencing, WM-Running Digits, WM-Digits Forward, WM-Digits Backward, WM-Symbol Span, WM-Spatial Addition and WM-Letter-Number Sequencing, were all low. See Online Appendix Figure 3A, Table 2A, & Figure 4A
$4b_1$	Good global model fit, all standardized path coefficients of *g* with subtests were statistically significant (*p* < .0001); standardized group factor coefficients for PR-Matrix Reasoning, PR-Figure Weights, PR-Set Relations, WM-Digit Sequencing, and WM-Letter Number Sequencing were all statistically significant (*p* < .05) but low; standardized group factor path coefficients for PR–Arithmetic, WM–Symbol Span, and WM–Spatial Addition were not statistically significant (*p* > .05). See Online Appendix Figure 5A, Table 3A, & Figure 6A
$4h_2$	Adequate global model fit, standardized *g*–PR path coefficient (.942) and *g*–WM path coefficient (.935) were very high and indicated poor discriminant validity; SLT standardized path coefficients for PR-Block Design, PR-Visual Puzzles, PR-Matrix Reasoning, PR-Figure Weights, PR-Set Relations, WM-Arithmetic, WM-Digit Sequencing, WM-Running Digits, WM-Digits Forward, WM-Digits Backward, WM-Symbol Span, WM-Spatial Addition and WM-Letter-Number Sequencing, were low. See Online Appendix Figure 7A, Table 4A, & Figure 8A
$4b_2$	Good global model fit, all standardized path coefficients of *g* with subtests were statistically significant (*p* < .0001); standardized group factor coefficients for PR-Block Design, PR-Matrix Reasoning, PR-Figure Weights, PR-Set Relations, WM-Arithmetic, WM-Digit Sequencing, and WM-Letter Number Sequencing were all statistically significant (*p* < .05) but low; standardized group factor coefficients for WM–Symbol Span and WM–Spatial Addition were not statistically significant (*p* > .05). See Online Appendix Figure 9A, Table 5A, & Figure 10A
$4h_3$	Good global model fit, standardized *g*–PR path coefficient (.953) was very high and indicated poor discriminant validity; SLT standardized path coefficients for PR-Block Design, PR-Visual Puzzles, PR-Matrix Reasoning, PR-Figure Weights, PR-Set Relations, PR-Symbol Span, PR-Spatial Addition, WM-Running Digits, and WM-Digits Forward were low. See Figure 6, Table 7, & Figure 8.
$4b_3$	Good global model fit, all standardized path coefficients of *g* with subtests were statistically significant (*p* < .0001); standardized group factor path coefficients for PR-Matrix Reasoning, PR-Figure Weights, PR-Set Relations, WM-Arithmetic, WM-Digit Sequencing, and WM-Letter Number Sequencing were statistically significant (*p* < .05) but low; standardized group factor path coefficient for PR-Spatial Span was statistically significant but very low; group factor path coefficient for PR–Spatial Addition was not statistically significant (*p* > .05). See Figure 5, Table 6, & Figure 7.
5	Good global model fit, all standardized path coefficients were statistically significant (*p* < .0001), factor correlations (.540-.941) were moderate to high and implied a general dimension requiring explication, $r_{\text{VS–FR}}$ = .941 indicated poor discriminant validity.
$5h_1$	Latent variable covariance matrix was not positive definite, standardized *g*–FR path coefficient (1.004) impermissible, Improper solution, model estimates not reported. This model is the implied model based on subtest construction, description, and assignment according to Wechsler et al. (2024); but which was *not* examined in CFA or reported. See Online Appendix Figure 11A

Table 5 continues

Table 5 continued

Model	Global Fit, Local Fit, and Parameter Estimate Problems
$5b_1$	Good global model fit; all standardized path coefficients of *g* with subtests were statistically significant ($p < .0001$); standardized group factor coefficients for WM–Digit Sequencing and WM–Letter-Number Sequencing were statistically significant ($p < .05$) but low; standardized group factor coefficients for FR–Matrix Reasoning, FR–Figure Weights, FR–Arithmetic, FR–Set Relations, WM–Symbol Span, and WM–Spatial Addition were not statistically significant ($p > .05$). See Online Appendix Figure 12A, Table 6A, & Figure 13A
$5h_2$	This is Model 5a reported in the WAIS–5 Technical and Interpretive Manual (Wechsler et al., 2024) and CFA starting point placing AR on WM *not* on FR as purportedly constructed. Adequate global model fit, standardized loading of *g*–FR (.992) indicated isomorphic relationship, FR indistinguishable from g, standardized loading of *g*–VS (.933) and *g*–WM (.910) were very high indicating poor discriminant validity; SLT standardized path coefficients for VS-Block Design, VS-Visual Puzzles, were low; SLT standardized path coefficients for FR-Matrix Reasoning, FR-Figure Weights, and FR-Set Relations were very low. See Online Appendix Figure 14A, Table 7A, & Figure 15A
$5b_2$	Good global model fit, all standardized *g* loadings with subtests were statistically significant ($p < .0001$); standardized group factor coefficients for VS–Block Design, VS–Visual Puzzles, WM–Arithmetic, and WM–Digit Sequencing were statistically significant ($p < .05$) but low, standardized group factor coefficients for FR–Matrix Reasoning, FR–Figure Weights, FR–Set Relations, WM–Symbol Span, and WM–Spatial Addition were not statistically significant ($p > .05$). See Online Appendix Figure 16A, Table 8A, & Figure 17A
$5h_3$	Good global model fit, standardized loading of *g*–VS (.985) and *g*–FR (.987) were very high and indicated poor discriminant validity; SLT standardized path coefficients for VS-Block Design, VS-Visual Puzzles, VS-Symbol Span, VS-Spatial Addition, FR-Matrix Reasoning, FR-Figure Weights, and FR-Set Relations were low. See Online Appendix Figure 18A, Table 9A, & Figure 19A
$5b_3$	Residual covariance matrix was not positive definite, Visual Puzzles had a negative residual variance estimate (-.155), Improper solution, model estimates not reported. See Online Appendix Figure 20A

Note. Model number indicates the number of group factors included in the model. Models specified by only the number are oblique, models with "h" specification are higher-order, and models with "b" specification are bifactor representations. V = Verbal, P = Performance, PS = Processing Speed, VC = Verbal Comprehension, PR = Perceptual Reasoning, WM = Working Memory, VS = Visual Spatial, FR = Fluid Reasoning. SLT = Schmid-Leiman Transformation. Subtest assignments to latent factors are specified in Figures 2 and 3.

Table 6

Sources of Variance in the Wechsler Adult Intelligence Scale–Fifth Edition (WAIS–5) 20 Subtests CFA According to a Bifactor Model (4b₃) with Four First–Order (Group) Factors for the Total Standardization Sample (N = 2,020)

	General		Verbal Comprehension		Perceptual Reasoning		Working Memory		Processing Speed				
WAIS–5 Subtest	*b*	S^2	*b*	S^2	*b*	S^2	*b*	S^2	*b*	S^2	h^2	u^2	*ECV*
Similarities	.661	.437	.401	.161							.598	.402	.731
Vocabulary	.655	.429	.569	.324							.753	.247	.570
Information	.647	.419	.466	.217							.636	.364	.658
Comprehension	.658	.433	.441	.194							.627	.373	.690
Block Design	.679	.461			.304	.092					.553	.447	.833
Visual Puzzles	.694	.482			.432	.187					.668	.332	.721
Matrix Reasoning	.707	.500			.250	.062					.562	.438	.889
Figure Weights	.761	.579			.205	.042					.621	.379	.932
Arithmetic	.758	.575					.134	.018			.593	.407	.970
Set Relations	.684	.468			.121	.015					.482	.518	.970
Digit Sequencing	.666	.444					.207	.043			.486	.514	.912
Running Digits	.413	.171					.425	.181			.351	.649	.486
Digits Forward	.502	.252					.641	.411			.663	.337	.380
Digits Backward	.623	.388					.393	.154			.543	.457	.715
Symbol Span	.664	.441			.091	.008					.449	.551	.982
Spatial Addition	.727	.529			.019	.000					.529	.471	.999
Letter-Number Sequencing	.674	.454					.281	.079			.533	.467	.852
Coding	.565	.319							.680	.462	.782	.218	.408
Symbol Search	.588	.346							.468	.219	.565	.435	.612
Naming Speed Quantity	.433	.187							.332	.110	.298	.702	.630
Total Variance		.416		.045		.020		.044		.040	.565	.435	
ECV		.736		.079		.036		.078		.070			
ω		.953		.882		.893		.861		.776			
ω_H/ω_{HS}		.887		.299		.069		.212		.361			
Relative ω		.931		.339		.077		.247		.465			
Factor Correlation		.942		.547		.263		.461		.601			
H		.939		.543		.318		.555		.558			
PUC		.763											
FDI		.969		.737		.564		.745		.747			

Note. *b* = standardized loading of subtest on factor, S^2 = variance explained, h^2 = communality, u^2 = uniqueness, ECV = explained common variance, ω = Omega, ω_H = Omega-hierarchical (general factor), ω_{HS} = Omega-hierarchical subscale (group factors), *H* = construct reliability index, PUC = percentage of uncontaminated correlations, FDI = factor determinacy index. Light shaded cells indicate minimum standard met; dark shaded cells indicate preferred/desired standard met.

Table 7

Sources of Variance in the Wechsler Adult Intelligence Scale–Fifth Edition (WAIS–5) 20 Subtests CFA According to a Schmid-Leiman Orthogonalized Higher-Order Factor Model (4h3) with Four First–Order (Group) Factors for the Total Standardization Sample (N = 2,020)

	General		Verbal Comprehension		Perceptual Reasoning		Working Memory		Processing Speed				
WAIS–5 Subtest	*b*	S^2	*b*	S^2	*b*	S^2	*b*	S^2	*b*	S^2	h^2	u^2	*ECV*
Similarities	.646	.417	.442	.195							.613	.387	.681
Vocabulary	.696	.484	.477	.228							.712	.288	.680
Information	.657	.432	.450	.203							.634	.366	.681
Comprehension	.661	.437	.453	.205							.642	.358	.680
Block Design	.696	.484			.221	.049					.533	.467	.908
Visual Puzzles	.724	.524			.230	.053					.577	.423	.908
Matrix Reasoning	.714	.510			.227	.052					.561	.439	.908
Figure Weights	.754	.569			.240	.058					.626	.374	.908
Arithmetic	.690	.476					.349	.122			.598	.402	.796
Set Relations	.667	.445			.212	.045					.490	.510	.908
Digit Sequencing	.637	.406					.323	.104			.510	.490	.795
Running Digits	.464	.215					.235	.055			.271	.729	.796
Digits Forward	.583	.340					.296	.088			.428	.572	.795
Digits Backward	.645	.416					.327	.107			.523	.477	.796
Symbol Span	.641	.411			.204	.042					.452	.548	.908
Spatial Addition	.679	.461			.216	.047					.508	.492	.908
Letter-Number Sequencing	.665	.442					.337	.114			.556	.444	.796
Coding	.584	.341							.561	.315	.656	.344	.520
Symbol Search	.573	.328							.551	.304	.632	.368	.520
Naming Speed Quantity	.403	.162							.387	.150	.312	.688	.520
Total Variance		.415		.042		.017		.029		.038	.542	.458	
ECV		.766		.077		.032		.054		.071			
ω		.950		.881		.889		.846		.770			
ω_H/ω_{HS}		.888		.281		.082		.173		.370			
Relative ω		.934		.319		.092		.204		.480			
Factor Correlation		.942		.531		.286		.416		.608			
H		.938		.512		.266		.397		.517			
PUC		.763											
FDI		.968		.716		.516		.630		.719			

Note. *b* = standardized loading of subtest on factor, S^2 = variance explained, h^2 = communality, u^2 = uniqueness, ECV = explained common variance, ω = Omega, ω_H = Omega-hierarchical (general factor), ω_{HS} = Omega-hierarchical subscale (group factors), *H* = construct reliability index, PUC = percentage of uncontaminated correlations, FDI = factor determinacy index. Light shaded cells indicate minimum standard met; dark shaded cells indicate preferred/desired standard met.