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What Does the WAIS-5 Measure? Insights From Exploratory Graph (Network) Analysis

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Abstract

The US version of the Wechsler Adult Intelligence Scale-Fifth Edition (WAIS-5; Wechsler, 2024) represents a recent revision to one of the most popular assessment instruments used in clinical settings across a variety of practice contexts. Evidence presented in the WAIS-5 Technical and Interpretive Manual supports this structure primarily through confirmatory factor analytic methods. Exploratory graph analysis (EGA) provides an alternative network psychometric approach to dimensionality assessment that does not require observed associations among scores to be attributed to common latent causes. The present investigation applied EGA to the WAIS-5 normative subtest correlation matrix based on 2,020 individuals ages 16:0-90:11. Separate analyses were conducted for the 10 primary subtests and all 20 subtests in the total battery. For the 10 primary subtests, the optimized EGA solution contained three dimensions, which was recovered in 79.8% of bootstrap replications and demonstrated excellent fit when subsequently evaluated using confirmatory factor analysis. For the 20-subtest total battery, a four-dimensional structure was recovered in 84.5% of bootstrap replications. Although several dimensions were highly stable, indicators associated with Working Memory and Fluid Reasoning exhibited substantial cross-dimensional instability. Collectively, these results did not fully reproduce the five-factor interpretive structure proposed for the instrument. Implications for WAIS-5 clinical use and interpretation are discussed.

Keywords: WAIS-5, structural validity, exploratory graph analysis, network psychometrics

What Does the WAIS-5 Measure? Insights From Exploratory Graph (Network) Analysis

Since their inception, the Wechsler Scales in general and the Wechsler Adult Intelligence Scale (WAIS) have occupied a prominent position in the assessment of human cognitive ability with historical reviews and surveys indicating that they are some of the most common assessments administered in clinical practice across a variety of contexts and specialties (e.g., Camara et al., 2000; Hartman, 2009). To wit, their scores are routinely used to describe cognitive functioning and inform consequential clinical, educational, and diagnostic decisions. Accordingly, evidence regarding the validity of the interpretations derived from these scores is of substantial importance for psychological assessment research and training writ large (McGill et al., 2021). One important source of validation evidence that is necessary for determining how those scores should be used and interpreted in clinical practice is evidence for internal structure (e.g., structural validity), or the extent to which relationships among test scores correspond with the dimensional organization of the constructs the instrument is intended to measure (American Educational Research Association et al., 2014). As noted by Canivez (2025a), structural validity evidence provides the empirical foundation for linking test scores to viable psychological constructs and is an important source of evidence for informing confidant clinical score interpretation. Thus, while the psychometric procedures used to investigate this aspect of construct validity (e.g., factor analysis) can appear to be mathematically esoteric, they are of primary importance as part of the broader test validation process (Strauss & Smith, 2009; Wasserman & Bracken, 2013).

Wechsler Adult Intelligence Scale-Fifth Edition (WAIS-5)

The US version of the Wechsler Adult Intelligence Scale-Fifth Edition (WAIS-5; Wechsler, 2024) represents a substantial revision of its predecessor. According to the Technical

Manual (Wechsler et al., 2024), two subtests from the previous addition were deleted and five new subtests were added significantly altering how the Working Memory indicators are conceptualized and scored. However, the most substantive change was altering the primary scoring/interpretive framework for the instrument from a four-factor primary index model to a five-factor primary index model to seemingly align with changes made to the Wechsler Intelligence Scale for Children- Fifth Edition (Wechsler, 2014). Structurally, the WAIS-5 is composed of 10 "primary" subtests (Vocabulary, Similarities [SI], Block Design [BD], Visual Puzzles [VP], Matrix Reasoning [MR], Figure Weights [FW], Digit Sequencing [DQ], Running Digits [FD], Coding [CD], and Symbol Search [SS]) that combine to form five primary index-level scores (Verbal Comprehension [VC], Fluid Reasoning [FR], Visual-Spatial [VS], Working Memory [WM], and Processing Speed [PS]) as well as an omnibus FSIQ composite[1]. Additionally, 10 "secondary" subtests (Information [IN], Comprehension [CO], Picture Concepts [PC], Arithmetic [AR], Set-Relations [SR], Digits Forward [DF], Digits Backward [DB], Letter-Number Sequencing [LN], Symbol Span [SSP], Spatial Addition [SA], and Naming Speed Quantity [NSQ]) can be combined with selected primary subtests to form a panoply of ancillary index and composite scores.[2] Whereas one of the primary or secondary subtests can be used as a substitute for an invalid or missing test for the calculation of the FSIQ, substitution is not permitted for any of the primary or ancillary index scores. Information for being able to discern what presumed "narrow" abilities are thought to measured by the primary and secondary subtests can be found in descriptions provided in the Technical Manual (pp. 9-15) as well as independent

[1]The FSIQ is composed of seven primary "FSIQ" subtests (Vocabulary, SI, BD, MR, FW, DQ, and CD) and is thought to be a proxy for psychometric *g*.

[2] As these scores do not contribute to the measurement of intelligence, they are not included in the present investigation, nor were they effectively modeled as part of the WAIS-5 structural validation reported in the Technical Manual.

interpretive resources that have examined historical variations of these measures in previously published test batteries (e.g., McGrew & Flanagan, 1998).

According to the Technical Manual (Wechsler et al., 2024), this organization reflects influences from contemporary hierarchical conceptualizations of intelligence in which a broad general dimension coexists with distinguishable cognitive abilities (e.g., Carroll, 1993). Further the Technical Manual notes that structural models of intelligence generally support hierarchical arrangements containing a general dimension at the apex and broad abilities at lower levels. The revision therefore continues the evolution of the Wechsler Scales toward more differentiated measurement of VC, VS, FR, WM, and PS which has been a target design goal dating back to the previous version of the measurement instrument (McGill et al., 2025). However, theoretical perspectives that do not necessarily attribute the positive manifold among cognitive tests exclusively to common latent causes. As an example, network theories conceptualize cognitive performance as emerging from interactions among underlying abilities and processes via a *bottom-up* perspective (Borsboom et al., 2021).

From this perspective, cognitive tasks can be represented as *nodes* connected according to their direct statistical relationships (i.e., *edges*), and strongly interconnected nodes may form identifiable clusters which can be interpreted as representing clusters associated with the conventional primary index scores and their theoretical psychological attributes (Fried, 2020). To wit, the WAIS-5 Technical Manual explicitly identifies network theories, along with process overlap theory (Kovacs & Conway, 2016), as contemporary perspectives relevant to understanding human intelligence in general and performance on the WAIS-5 in particular. This theoretical expansion is consequential for the evaluation of the WAIS-5 internal structure because different psychometric models embody different assumptions regarding why cognitive

scores may covary. Unfortunately, the results of these analyses, if conducted, have yet to be reported.

Structural Validity of the WAIS-5

Factor analysis has traditionally served as the principal method for investigating the internal structure of commercial ability measures (Dombrowski & McGill, 2024). Put simply, factor analytic models assume that associations among observed variables can be explained by one or more unobserved latent variables regardless of whether an exploratory or confirmatory method is preferred.[3] Confirmatory factor analysis (CFA), evaluates how well a prespecified measurement structure reproduces the observed covariance matrix. CFA is therefore considered to be more useful when investigators possess strong theoretical expectations regarding the number of dimensions and the indicators associated with them (Schmitt, 2011). Accordingly, the internal structure of the WAIS-5 was primarily evaluated using CFA procedures and generally supportive of the five-factor interpretive structure preferred by the test publisher. Though as Canivez and colleagues (2026) note, the final validation model required the specification of several departures from desired simple structure (e.g., cross-loadings, correlated residual terms) that do not cohere with the more simplified scoring framework given to test users.

Nevertheless, establishing that a theoretically specified model can adequately reproduce observed correlations is not equivalent to demonstrating that the same dimensional organization would emerge when fewer structural restrictions are imposed (Greene et al., 2023). This distinction is especially relevant when several plausible representations of a complex construct may fit the same data. Exploratory approaches can therefore provide complementary evidence by

[3] It should be noted that in the WAIS-5 Technical Manual (Wechsler et al., 2024), exploratory factor analysis (EFA) was eschewed because of a clear preference for CFA as the prevailing structural validation technique (please see p. 77 for the rationale employed).

asking what organization emerges from relationships among the observed indicators without requiring their assignment to a predetermined structure (Flora & Flake, 2017).

This overreliance on CFA to procure models that are not able to be replicated has figured prominently in investigations of previous Wechsler Scales. Independent research on the WISC-V, for example, has produced disagreement regarding whether its subtests support the five-factor structure favored by its publisher or a more parsimonious four-dimensional organization in which VS and FR abilities are less clearly differentiated in accord with prior Wechsler score configurations in terms of their previous cohesion into a coherent Perceptual Reasoning (PR) dimension (e.g., Canivez et al., 2016, 2017; Watkins et al., 2023). It should be noted that these investigations have used best practices in EFA, CFA, and network analyses using the same normative data that was the target of the validation studies reported in the WISC-V Technical Manual (Wechsler, 2014). Further, concerns about the whether the Wechsler Scales are best represented by a four- or a five-factor structure can be traced to a special issue of the *Journal of Psychoeducational Assessment* (JPA; Tobin, 2013) in which a hypothetical five-factor model was fit to the WISC-IV and WAIS-IV respectively for the first time. Whereas the five-factor model seemed plausible from a theoretical and global fit perspective, notable commentaries pointed out that there was seemingly evidence of model misspecification to fit those models (see Canivez, & Kush [2013] for further commentary on the matter). Further complicating the matter are additional independent CFA investigations of the WAIS-IV which suggested a five-factor model albeit one which departed from those reported in the JPA special issue studies (e.g., Benson et al., 2010).

Of concern, Canivez et al. (2026) recently produced the first independent attempt to recover the presumed WAIS-5 structure via EFA and CFA and found further evidence supporting

a more circumspect four-factor model that departed from publisher theory in several significant ways. First, the previously described VS and FR fusion remained an issue in their modeling attempts (as per Canivez & Kush, 2013). Second and most prominent, the assignment of the newly designed WM measures was complicated in that a coherent WM factor evaded coherent assignment despite numerous iterations attempting to model it. These results suggest that uncovering the underlying structure of the WAIS-5 may be even more complicated than that of its child-age predecessor and thus requiring attempts to explore via different methods to establish a coherent nomological network (Cronbach & Meehl, 1955; McGrew et al., 2023).

Exploratory Graph Analysis (EGA)

As previously mentioned, developments in network psychometrics provide another approach for investigating dimensionality (Isvoranu et al., 2022). Rather than modeling associations among test scores as consequences of common latent variables, network models focus on direct relationships among observed scores. Tests or items are represented as nodes, whereas edges represent relationships between nodes after conditioning on the remaining variables in the network. Golino and Epskamp (2017) developed exploratory graph analysis (EGA) as a method for estimating dimensionality from such networks. EGA identifies communities of strongly interconnected nodes within the larger network. These communities can be interpreted as dimensions because indicators within a community demonstrate stronger relationships with one another than with indicators assigned to other communities.

Simulation research has supported EGA as a viable method for dimensionality assessment, and the procedure has increasingly been applied to cognitive ability data (Christensen & Golino, 2021; Cosemans et al., 2022; Golino & Epskamp, 2017). Unlike conventional EFA retention procedures, EGA simultaneously estimates dimensionality and the

allocation of indicators to dimensions. Bootstrap EGA further permits investigators to examine whether an identified dimensional structure is consistently recovered across repeated samples and whether individual indicators remain reliably assigned to the same communities which permits a form of internal replication of a recovered model without cross-validating the underlying sample (Christensen & Golino, 2021). The latter consideration is particularly important for multidimensional intelligence batteries as Monte Carlo simulations have demonstrated that recovered EFA and CFA solutions that depart from preferred theory may not replicate when subjected to resampling (Dombrowski et al., 2021). Thus, an apparently interpretable solution may nevertheless contain dimensions or individual subtests whose community assignments are unstable. Such instability provides information that cannot be obtained simply by selecting the best-fitting model from a set of predetermined structures (Montoya & Edwards, 2021).

Watkins et al. (2023) illustrated the potential utility of this approach with the WISC-V. Applying bootstrap EGA to the 10 primary WISC-V subtests in a large clinical sample, they identified four communities rather than the five dimensions represented by the publisher's primary scoring structure. Most notably, VS and FR subtests formed a common community. Their results provided converging evidence with previous factor analytic investigations suggesting that the scoring structure and empirical dimensional structure of the WISC-V may not be isomorphic. Consequently, the WAIS-5 presents a relevant target to extend this work given its prominent use within the broader assessment community. In addition to explicitly incorporating network perspectives into the theoretical discussion regarding its development in the Technical Manual, the WAIS-5 substantially expands measurement within several cognitive domains; most notably, WM. Consequently, the dimensional organization recovered from its primary battery

may not necessarily be identical to that obtained when the complete set of available subtests is considered. This distinction is important because dimensional recovery depends in part on adequate construct representation. A narrowly sampled domain may fail to emerge as a distinct community even when a broader collection of indicators permits greater differentiation (Christensen & Golino, 2021).

Purpose of the Current Study

The purpose of the present investigation was to examine the dimensional structure of the WAIS-5 using EGA. Rather than imposing the five-dimensional organization specified by the scoring model for the instrument, EGA was used to determine how WAIS-5 subtests organized into communities based on their conditional relationships. This approach permitted three related questions to be considered: (a) whether the five-dimensional WAIS-5 scoring structure would be recovered using an exploratory network approach, (b) whether the dimensional structure differed between the 10-primary-subtest and 20-subtest total configurations, and (c) whether the dimensions and subtest assignments identified by EGA were stable across resampling replications.

Methods

Participants

Participants included 2,200 adolescents and adults ages 16:0 to 90:11 from the US version WAIS-5 normative sample. This sample was obtained using a stratified sampling plan designed to accord with 2022 US census estimates. Inspection of the demographic data reported in the Technical Manual (Wechsler et al., 2024) reveal that the data for the normative sample were consistent with the US population parameters for age, gender, race/ethnicity, and

geographic region. All WAIS-5 measures were administered to participants by licensed clinical examiners or those with verified training in psychological assessment procedures.

Measurement Instrument

The WAIS-5 is an individually administered, norm-referenced, test of intellectual function for adolescents and adults. It is comprised of 20 primary and secondary subtests which combine to yield five primary index-level scores (VC, PR, VS, WM, and PS), as well as an omnibus FSIQ that is based on a differentially weighted combination of seven of the primary subtests. While all primary and secondary subtests are expressed as scaled scores ($M = 10$, $SD = 3$), primary index and composite scores are expressed as standard scores ($M = 100$, $SD = 15$). Extensive reliability and validity evidence for the measures are reported in the Technical Manual.

Procedure and Data Analyses

Target data for the investigation was the average intercorrelation matrix of WAIS-5 subtests for all ages as reported in Table 5.1 of the Technical Manual (Wechsler et al., 2024, pp. 74-75). Data analyses were performed using the *rempsyc* (Thériault, 2023) and *EGAnet* (v2.3.0, Golino & Christensen, 2025) packages in **R** (v4.5.1, R Core Team, 2025). Two analyses of the covariance matrix featuring the normative sample summary data were performed. The first analysis included the correlations of the 10 primary subtests. The second analysis utilized the correlations of all 20 WAIS-5 subtests. Both analyses followed the suggestions in Christensen and Golino (2021). First, the empirical EGA was estimated using Glasso extraction with the Walktrap algorithm for community detection. Gamma was set to .5. Second, the Walktrap algorithm has a hyperparameter, *t*, that can impact the ultimate result. *EGA.fit*, part of the *EGAnet* package that varies the value of *t*, was used to select the best model based on Total Entropy Fit Index (TEFI). For this aspect of the investigation, a range of *t* vales from 3 to 12 was

tested (as per Golino et al., 2021). Finally, the best EGA model indicated by *EGA.fit* was assessed for stability through bootstrap resampling with 5,000 iterations.

Results

10 Subtest "Primary" Battery

The empirical EGA of WAIS-5 core subtests indicated a single dimension with a TEFI of zero. The empirical network structure is shown in Figure 1. The *EGA.fit* analysis indicated that the best model resulted with a *t* of 4. This model had three dimensions and a TEFI of -4.18. The typical network structure from the bootstrap EGA is presented in Figure 2. The descriptive statistics for the bootstrap replications are presented in Table 1. The table shows that the median number of dimensions identified was three which is inconsistent with the empirical EGA findings. The confidence interval of .79 is small indicating a narrow range of outcomes. Table 2 shows the percentage of dimensions found in the 5,000 replications. The number of dimensions identified ranged from two to three with three being the most prevalent (79.8 percent) followed by two (20.2 percent).

To examine the stability of the EGA dimensions, the percentage of times the dimension is exactly replicated across the bootstraps can be examined. The results show that dimension 1 (VC) was replicated 76.7 percent of the time, dimension 2 (PR) 84.3 percent of the time, and dimension 3 (PS) 100 percent of the time. The subtest stability can be seen in Figure 3. The figure shows the percentage of times each subtest was assigned to its empirical dimension. Subtests with percentages below .75 can be considered problematic (Christensen & Golino, 2021). All subtests were assigned to their empirical dimension at or above 75 percent of the time. Table 3 presents the subtest assignments over the replications. Subtests that are assigned to multiple dimensions in substantial percentages (> 10%) can be viewed as empirically unstable.

SI, VC, and RD appear in two different dimensions at rates above 10% indicating that these subtests are likely inherently unstable. Follow-up CFA fit statistics comparing the empirical and typical configurations are reported in Table 4.

20 Subtest Total Battery

The empirical EGA of all WAIS-5 subtests indicated four dimensions and had a TEFI of -10.95. The empirical network structure is shown in Figure 4. The *EGA.fit* analysis indicated that the best model resulted with a *t* of 10. This model had four dimensions and a TEFI of -11.74. The typical network structure from the bootstrap EGA is presented in Figure 5. The descriptive statistics for the bootstrap replications are presented in Table 5. The table shows that the median number of dimensions identified was four consistent with the empirical EGA findings. The confidence interval of .75 is small indicating a narrow range of outcomes. Table 6 shows the percentage of dimensions found in the 5,000 replications. The number of dimensions identified ranged from three to six with four being the most prevalent (84.5 percent) followed by five (13.1 percent).

To examine the stability of the EGA dimensions, the percentage of times the dimension is exactly replicated across the bootstraps can be examined. Table 7 shows that dimensions 1 and 4 were replicated consistently whereas dimension 2 was highly unstable. The subtest stability can be seen in Figure 6. The figure shows the percentage of times each subtest was assigned to its empirical dimension. Subtests with percentages below .75 can be considered problematic (as per Christensen & Golino, 2021). Three subtests, SA, AR, and DQ have replication values below .75 with DQ having a very low percentage (36%) indicating a high degree of instability. Table 8 presents the subtest assignments over the replications. Subtests that are assigned to multiple dimensions in substantial percentages (> 10%) can be viewed as unstable. AR, DQ, SSP, SA,

and LN all appear in at least three different dimensions at rates above 10% indicating that these subtests are unstable. Taken together, these results indicate that SA, AR, and DQ are likely problematic indicators that will likely confound replication via arbitrary assignment in conventional CFA models or singular EFA runs using different estimation techniques (e.g., Dombrowski et al. 2019; Steiner & Grieder, 2020).

Table 9 shows the subtest assignments based on the publisher preferred CFA[4], empirical results, and typical results (CFA fit statistics are reported in Table 10 comparing the models). A main difference in these assignments is that the empirical and typical results have four dimensions while the publisher preferred CFA indicates five. The first dimension (VC) is identical in all the solutions. No other dimension is the same over the three solutions. However, the fourth dimension (PS) of the empirical and typical results is the same and represents the fifth dimension of the publisher preferred CFA with the addition of the CD subtest.

Discussion

The present investigation evaluated the structure of WAIS-5 variables using EGA, a network psychometric approach that does not require the relationships among subtests to conform to an a latent-variable structure that must be specified *a priori*. In total, the results did not reproduce the five-dimensional primary structure aligning with the scoring/interpretive model that is suggested for the instrument (e.g., Sattler et al., 2025). More importantly, these results suggest that conclusions regarding WAIS-5 dimensionality depend substantially on the breadth of indicators included in the analysis. When only the 10 primary subtests were considered, the optimized network contained three dimensions (hypothesized to represent VC,

[4] An important advantage of exploratory analytic methods such as EFA and EGA is that the analyst does not have to specify subtest cross-loadings in advance and risk under-fitting a model (Asparouhov & Muthén 2009).

PR, and PS). This structure was identified in nearly 80% of bootstrap replications and subsequently demonstrated excellent fit using CFA. In contrast, analysis of all 20 subtests resulted in four dimensions (hypothesized to represent VC, PR, WM, and PS), a solution recovered in approximately 85% of bootstrap replications. Thus, neither configuration supported five distinct communities corresponding with the five primary WAIS-5 index scores as a presumed complexly determined PR dimension would seemingly harken back a return to previous Wechsler scoring frameworks. Perhaps the most consequential finding concerns the 10 primary subtests. These subtests form the foundation of routine WAIS-5 administration and primary index interpretation (Wechsler et al., 2024), yet their network organization did not differentiate into the five domains implied by the scoring structure. The failure to recover five communities should not be interpreted as demonstrating that the corresponding cognitive constructs do not exist per se. Rather, it indicates that the direct statistical relationships among these 10 indicators do not naturally partition into five distinguishable communities under the present analytic framework.

Expanding the analysis to all 20 WAIS-5 subtests produced a more differentiated structure. Four rather than three dimensions emerged, and the four-dimensional solution was highly dominant across bootstrap samples. This finding suggests that increasing construct representation permits distinctions that are difficult to identify using only the primary battery (Goretzko et al., 2024). Yet the additional indicators did not result in recovery of the publisher's preferred five-dimensional organization (e.g., VC, VS, FR, WM, PS). Instead, the 20-subtest solution exhibited a pattern reminiscent of structural findings reported for previous Wechsler instruments (e.g., Canivez & Watkins, 2016). That is a four-dimension model (VC, PR, WM, PS) reminiscent of prior Wechsler score configurations; albeit, highly unstable in its composition.

Whereas the VC community was especially robust, the distinction between VS and FR abilities was less apparent. This result resembles findings from WISC-V structural investigations in which those dimensions fused together to form a complexly determined PR dimension which would seemingly obviate one of the most important design goals in the development of the recent iterations of the scales (McGill et al., 2025). To wit, Watkins et al. (2023) identified a four-community WISC-V structure in which this same fusion was observed in those dimensions, also using EGA, indicating that the results do not appear to be the product of method bias (McGrew et al., 2023). The recurrence of this pattern across Wechsler instruments warrants attention. The WAIS-5 explicitly retains separate VS and FR primary indexes, yet the present network results suggest that the distinction between these domains may be less pronounced at the level of observed subtest relationships than the recommended scoring model implies.

Instability of WM and FR Indicators

The bootstrap analyses provide an additional perspective that would be obscured by considering dimensionality alone. Although the 20-subtest solution consistently produced approximately four dimensions, one of those communities was reproduced exactly in only 26.5% of bootstrap samples. Several subtests also demonstrated substantial variation in community assignment. AR, DQ, SA, SS, and LN were particularly relevant in this regard as they all failed to meet the .75 indicator-stability criterion for indicator stability suggested by (Christensen & Golino, 2021). These findings suggest that some WAIS-5 subtests may occupy positions between broader cognitive communities rather than functioning as unambiguous markers of a single domain. This possibility is plausible given the complexity of many WAIS-5 tasks. Arithmetic, for example, requires quantitative reasoning while simultaneously imposing demands on attention, auditory processing, and working memory among other cognitive attributes. Users of the

Wechsler Scales would do well to consider the varied history of that indicator in terms of its varied assignment as a primary or supplementary subtest to an array of indexes seemingly with every new incarnation of a test (Canivez et al., 2026; McGill et al., 2025). As an example, AR was previously assigned as a primary measure to the former Freedom from Distractibility Index (a precursor to WM) on the WISC-III, dimension that no longer exists.[5]

Relation to Previous Wechsler Structural Research

The present findings also extend previous network research on the Wechsler scales. Watkins et al. (2023) used bootstrap EGA to investigate the 10 primary WISC-V subtests and recovered four communities rather than the five represented in the publisher's scoring structure. Their results were consistent with a substantial body of factor analytic research suggesting that VS and FR indicators were insufficiently differentiated to support separate first-order dimensions (Canivez, 2025b). The current results demonstrate that this issue persists in a different form with the WAIS-5. Despite changes in subtest composition and expanded construct representation, EGA again failed to recover five communities corresponding to the five primary Wechsler index domains. This is also consistent with the results furnished recently by Canivez and colleagues (2026) featuring independent EFA/CFA results for the WAIS-5. Notably those authors reported difficulty fitting the WM measures in addition to the FR measures highlighted in the current study in their analyses. As previously mentioned, the present results suggest that difficulty is likely a product of instability in those measures that was not known prior to their investigation using more a more constrained analytic approach (Asparouhov & Muthén 2009). There is, however, an important distinction. The 20-subtest WAIS-5 analysis suggests that dimensionality

[5]AR has not been featured as a primary subtest in either the WISC-IV (Wechsler, 2003) or the WISC-V (Wechsler, 2014).

itself is sensitive to the breadth of measurement. The primary battery yielded three dimensions whereas the complete battery yielded four. Consequently, discrepancies between theoretical and empirical structure cannot be understood solely as a question of choosing the "correct" number of dimensions (Epskamp et al., 2018). They may also reflect the extent to which a battery provides enough indicators to permit theoretically related abilities to differentiate statistically (Greene et al., 2023).

Provisional Implications for WAIS-5 Interpretation

The results should not be construed as invalidating the WAIS-5 or suggesting that its primary index scores are devoid of useful information. Structural validity represents one component of a larger validity argument, and different analytic models address different questions (Kane, 2013). While it is beyond the scope of the present study to attempt to adjudicate important differences in how the structure of intelligence *should* be represented given the explicit assumptions underlying the different methodological approaches (i.e., McGrew et al., 2023), the findings do raise questions about interpreting the five primary index scores as if they necessarily represent five empirically discrete psychological dimensions. This distinction is clinically important as a scoring system for an instrument is an interpretive framework rather than direct evidence of psychological structure (McNally, 2021). When the scoring and empirical structures diverge, interpretation should be calibrated to the strength of the available validity evidence rather than to the apparent precision afforded by the score report (Dombrowski et al., 2022).

While the Technical Manual acknowledges network and process-overlap perspectives in which performance emerges through interactions among multiple cognitive processes rather than through isolated operation of discrete abilities, such complexity creates difficulties when these measures are used as components of narrowly defined composite scores (McGill et al., 2018). A

composite interpretation assumes that its constituent indicators share sufficient construct-relevant variance to warrant aggregation and that the resulting score can meaningfully be distinguished from alternative composites (Breit et al., 2024). The present results suggest that those assumptions deserve additional investigation for some WAIS-5 domains.

Study Limitations

As with any study, several limitations qualify the present findings. First, the analyses were conducted using the average subtest correlation matrix reported in the WAIS-5 Technical Manual rather than participant-level data. Accordingly, the bootstrap procedure operates from the available correlation structure rather than resampling the original normative cases. Access to individual-level standardization data would permit additional analyses and potentially more direct evaluation of sampling variability though access to those data is presently commercially embargoed. As these results represent a static examination of the WAIS-5 overall normative sample at a single point in time, future research featuring these data would be instructive for determining the degree to which presumed WAIS-5 scores are invariant across relevant clinical conditions and/or demographic groups.

Second, the analyzed correlation matrix combines individuals across a very broad age range. The structure of cognitive abilities may not be invariant across this developmental span (Tucker-Drob, 2009). Consequently, future EGA studies should therefore examine dimensional structure within age strata and evaluate whether community composition changes systematically across the adult lifespan. Third, EGA represents one approach to dimensionality assessment. Its results should be integrated with evidence obtained from EFA, CFA, bifactor modeling, multidimensional scaling, and other structural methods rather than treated as uniquely dispositive (McGrew et al., 2023). Convergence across methods based on different assumptions would

provide stronger evidence regarding the organization of WAIS-5 scores than any single analytic approach. Finally, the present analyses concern the normative sample. Structural relationships may differ in clinical populations, particularly when neurological, developmental, psychiatric, or other conditions alter the covariance among cognitive processes (Lezak et al., 2012). Replication using clinical samples will therefore be necessary before assuming that the present communities generalize to populations for whom the WAIS-5 is frequently administered.

Conclusion

The WAIS-5 represents a major revision of one of the most consequential instruments in psychological assessment. Its primary scoring/theoretical framework organizes cognitive performance into five domains, yet the present exploratory network analyses did not recover this five-dimensional structure. Collectively, these findings suggest that the WAIS-5 scoring structure, and its empirically recovered network structure are not isomorphic. They also demonstrate that conclusions about dimensionality depend partly on the breadth with which cognitive constructs are represented in the battery which may or may not be represented in an instrument's suggested scoring structure (e.g., Kaufman, 1994). Given the prominent role of WAIS-5 scores in psychological assessment, continued independent investigation of these structural relationships using complementary psychometric methods is warranted given its lifecycle is relatively new (Beaujean, 2015).

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Table 1

Descriptive Statistics for Bootstrap Replication Dimensions of Primary Subtests

Replications	Median Dimensions	SE	CI.dim	95% CI
5,000	3.00	0.40	0.79	[2.21, 3.79]

Note. CI.dim = Median dimensional confidence interval.

Table 2

Percentage of Dimensions Across Bootstrap Replications of Primary Subtests

Dimensions	Percentage
2.00	20.2
3.00	79.8

Table 3

Primary Subtest Stability Across Replications

	Dimension		
Subtest	1(VC)	2 (PR?)	3 (PS)
SI	0.798	0.202	
VC	0.798	0.202	
BD		1.000	
VP		1.000	
MR		1.000	
FW		1.000	
DQ	0.003	0.997	
RD	0.768	0.232	
CD			1.000
SS			1.000

Note. Zero values have been omitted for table clarity. SI = Similarities, VC = Vocabulary, BD = Block Design, VP = Visual Puzzles, MR = Matrix Reasoning, FW = Figure Weights, DQ = Digital Sequencing, RD = Running Digits, CD = Coding, SS = Symbol Search. VC = Verbal Comprehension, PR = Perceptual Reasoning, PS = Processing Speed.

Table 4

CFA Results for Primary Empirical and Typical Network Structures for the 10 Primary Configuration

Model	χ^2	*df*	χ^2/df	*p*	CFI	TLI	RMSEA [90% CI]	SRMR	AIC	BIC
Empirical	1,053.06	35	30.09	<.001	.88	.85	.12 [.11, .13]	.06	49,632.62	49,744.83
Typical	175.09	32	5.47	<.001	.98	.98	.05 [.04, .05]	.03	48,760.65	48,889.70

Note. CFI = comparative fit index; TLI = Tucker-Lewis index, SRMR = standardized root mean square residual; RMSEA = root mean square error of approximation; AIC = Akaike information criterion, BIC = Bayesian information criterion.

Table 5

Descriptive Statistics for Bootstrap Replication Dimensions for All Subtests

Replications	Median Dimensions	SE	CI.dim	95% CI
5,000	4.00	0.38	0.75	[3.25, 4.75]

Note. CI.dim = Median dimensional confidence interval.

Table 6

Percentage of Dimensions Across Bootstrap Replications for All Subtests

Dimensions	Percentage
3.00	2.2
4.00	84.5
5.00	13.1
6.00	0.2

Table 7

Dimension Stability Over Replications for All Subtests

Dimension	Percentage
1	99.9
2	26.5
3	75.7
4	100

Note. Dimensional interpretation is as follows: 1 = Verbal Comprehension, 2 = Perceptual Reasoning, 3 = Working Memory, 4 = Processing Speed.

Table 8

Subtest Stability Across Replications for All Subtests

	Dimension					
Subtest	1(VC)	2 (PR?)	3 (WM)	4 (PS)	5 (?)	6 (?)
SI	1.000					
VC	1.000					
IN	1.000					
CO	1.000					
BD		0.985			0.015	
VP		0.994			0.006	
MR		0.992			0.007	
FW		0.992			0.008	
AR		0.675	0.215		0.109	
SR	0.023	0.961	0.007		0.009	
DQ		0.364	0.486	0.001	0.149	0.001
RD		0.021	0.935		0.044	
DF		0.021	0.935		0.044	
DB		0.036	0.910		0.053	
SSP		0.768	0.096	0.001	0.135	0.001
SA		0.727	0.130	0.001	0.140	0.001
LN		0.123	0.758		0.118	0.001
CD				1.000		
SS				1.000		
NSQ				1.000		

Note. Zero values have been omitted for table clarity. SI = Similarities, VC = Vocabulary, IN = Information, CO = Comprehension, BD = Block Design, VP = Visual Puzzles, MR = Matrix Reasoning, FW = Figure Weights, AR = Arithmetic, SR = Set Relations, DQ = Digital Sequencing, RD = Running Digits, DF = Digits Forward, DB = Digits Backward, SSP = Symbol Span, SA = Spatial Addition, LN = Letter-Number Sequencing, CD = Coding, SS = Symbol Search, NSQ = Naming Speed Quantity. VC = Verbal Comprehension, VS = Visual-Spatial, WM = Working Memory, PS = Processing Speed, PR = Perceptual Reasoning, ? = likely spurious dimension given the low weights that prevent coherent identification.

Table 9

WAIS 5 Dimension Assignments

Subtest	Publisher	Empirical	Typical
SI	1 (VC)	1	1
VC	1	1	1
IN	1	1	1
CO	1	1	1
BD	2 (VS)	2 (PR?)	2 (PR?)
VP	2	2	2
MR	3 (FR)	2	2
FW	3	2	2
AR	3	3	2
SR	3	2	2
DQ	4 (WM)	3	2
RD	4	3	3
DF	4	3	3
DB	4	3	3
SSP	4	2	2
SA	4	2	2
LN	4	3	3
CD	5 (PS)	4	4
SS	5	4	4
NSQ	5	4	4

Note. SI = Similarities, VC = Vocabulary, IN = Information, CO = Comprehension, BD = Block Design, VP = Visual Puzzles, MR = Matrix Reasoning, FW = Figure Weights, AR = Arithmetic, SR = Set Relations, DQ = Digital Sequencing, RD = Running Digits, DF = Digits Forward, DB = Digits Backward, SSP = Symbol Span, SA = Spatial Addition, LN = Letter-Number Sequencing, CD = Coding, SS = Symbol Search, NSQ = Naming Speed Quantity. VC = Verbal Comprehension, VS = Visual-Spatial, FR = Fluid Reasoning, WM = Working Memory, PS = Processing Speed, PR = Perceptual Reasoning.

Table 10

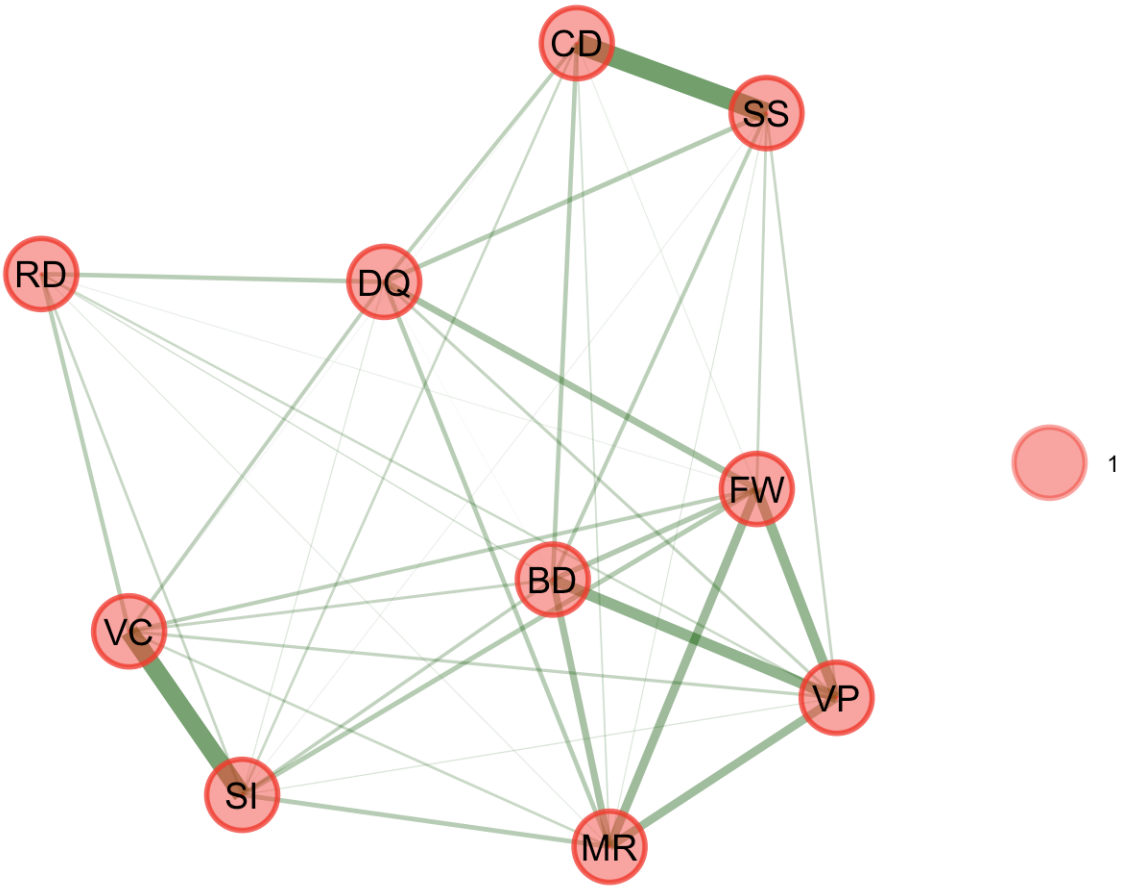
CFA Results for All Subtests Empirical and Typical Network Structures

Model	χ^2	*df*	χ^2/df	*p*	CFI	TLI	RMSEA [90% CI]	SRMR	AIC	BIC
Empirical	1,055.25	164	6.43	< .001	.96	.95	.05 [.05, .06]	.03	94,035.26	94,293.36
Typical	1,141.32	164	6.96	< .001	.95	.95	.05 [.05, .06]	.04	94,121.33	94,379.43

Note. CFI = comparative fit index; TLI = Tucker-Lewis index, SRMR = standardized root mean square residual; RMSEA = root mean square error of approximation; AIC = Akaike information criterion, BIC = Bayesian information criterion.

Figure 1

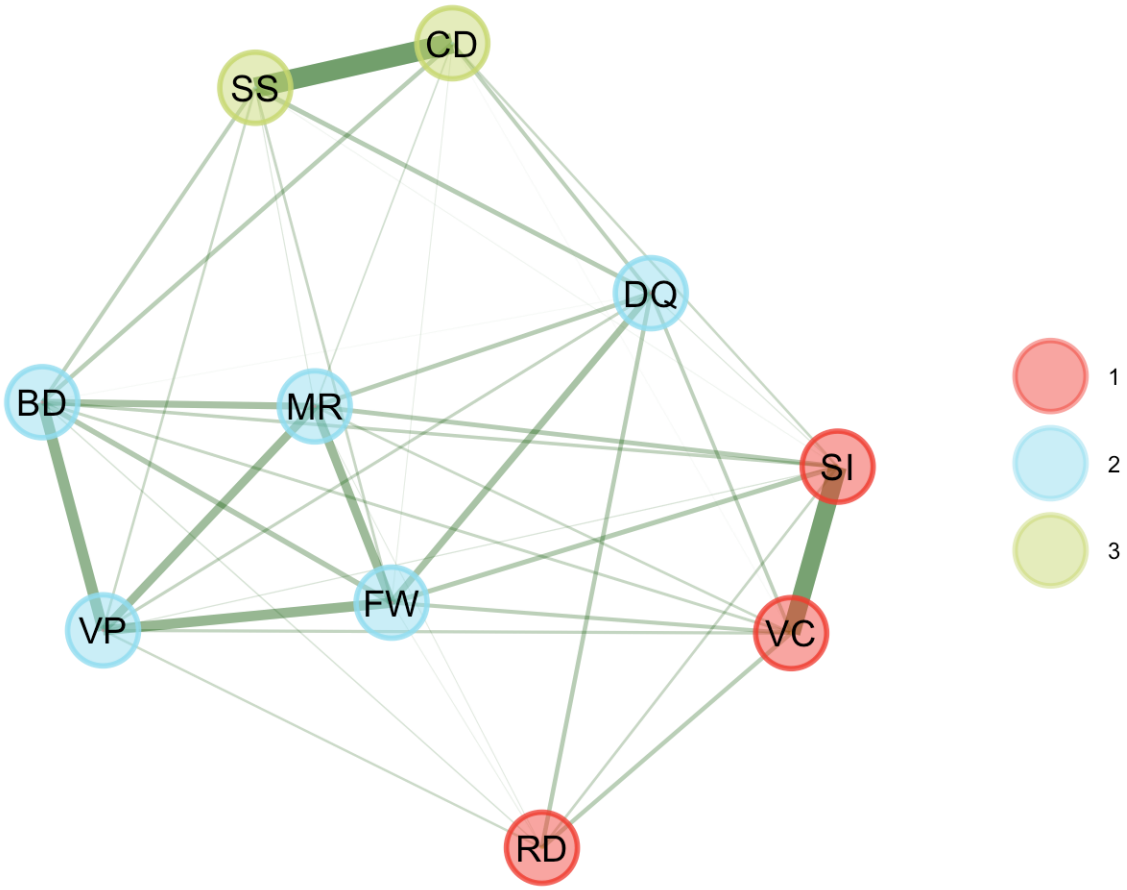
Empirical Network Structure of WAIS-5 Primary Subtests



Note. Zero values have been omitted for table clarity. SI = Similarities, VC = Vocabulary, BD = Block Design, VP = Visual Puzzles, MR = Matrix Reasoning, FW = Figure Weights, DQ = Digital Sequencing, RD = Running Digits, CD = Coding, SS = Symbol Search. Dimension 1 in these analyses is regarded as representing omnibus general intelligence.

Figure 2

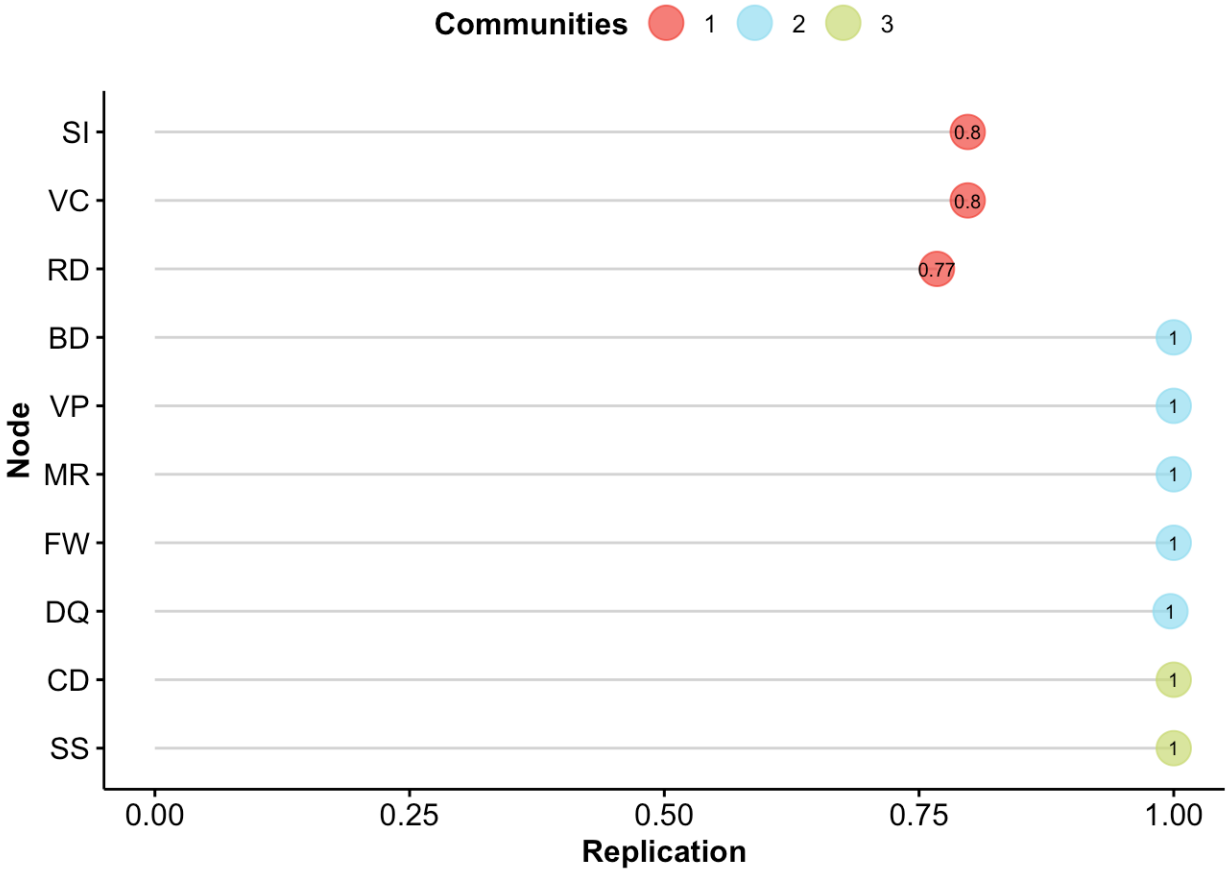
Typical Network Structure of WAIS-5 Primary Subtests



Note. Zero values have been omitted for table clarity. SI = Similarities, VC = Vocabulary, BD = Block Design, VP = Visual Puzzles, MR = Matrix Reasoning, FW = Figure Weights, DQ = Digital Sequencing, RD = Running Digits, CD = Coding, SS = Symbol Search, 1 = Verbal Comprehension, 2 = Perceptual Reasoning, 3 = Processing Speed.

Figure 3

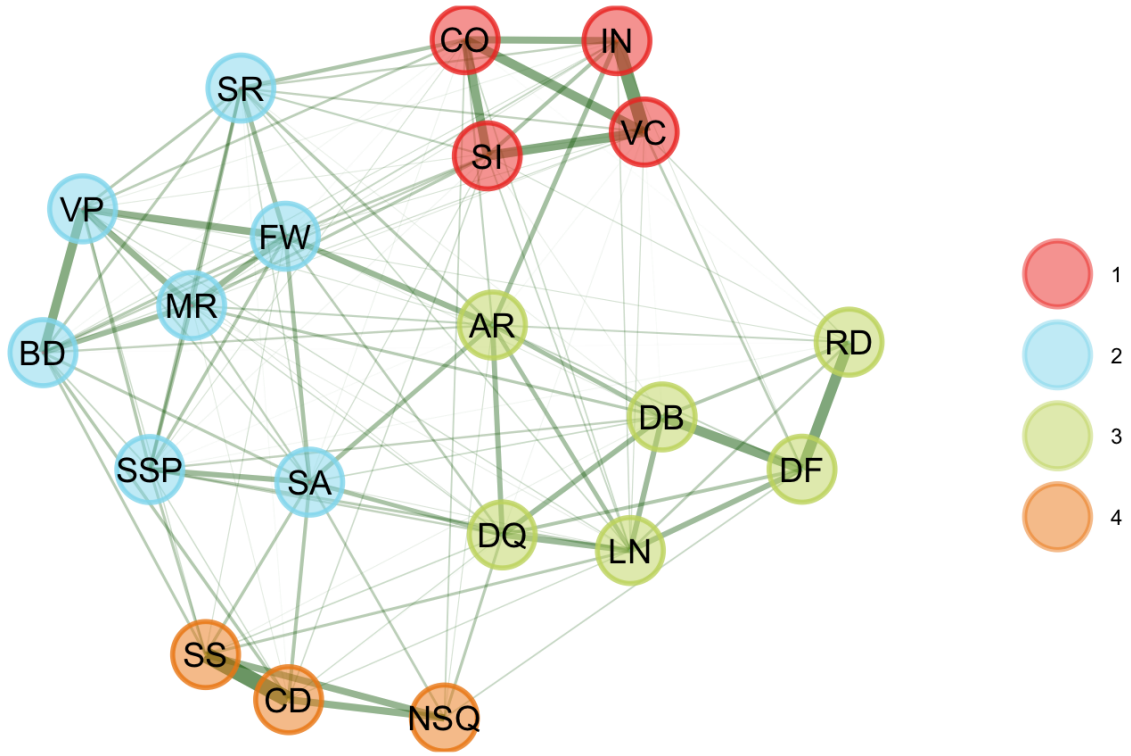
Primary Subtest Assignment Stability Over Replications



Note. Zero values have been omitted for table clarity. SI = Similarities, VC = Vocabulary, BD = Block Design, VP = Visual Puzzles, MR = Matrix Reasoning, FW = Figure Weights, DQ = Digital Sequencing, RD = Running Digits, CD = Coding, SS = Symbol Search, 1= Verbal Comprehension, 2 = Perceptual Reasoning, 3 = Processing Speed.

Figure 4

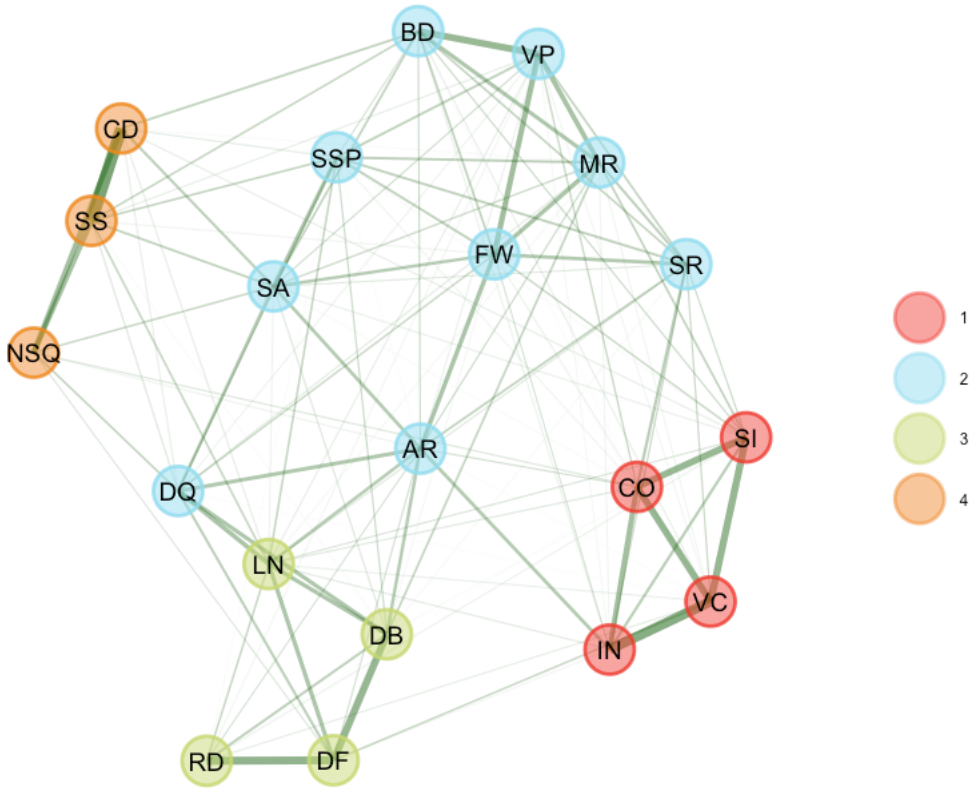
Empirical Network Structure of All WAIS-5 Subtests



Note. Zero values have been omitted for table clarity. SI = Similarities, VC = Vocabulary, IN = Information, CO = Comprehension, BD = Block Design, VP = Visual Puzzles, MR = Matrix Reasoning, FW = Figure Weights, AR = Arithmetic, SR = Set Relations, DQ = Digital Sequencing, RD = Running Digits, DF = Digits Forward, DB = Digits Backward, SSP = Symbol Span, SA = Spatial Addition, LN = Letter-Number Sequencing, CD = Coding, SS = Symbol Search, NSQ = Naming Speed Quantity, 1= Verbal Comprehension, 2 = Perceptual Reasoning, 3= Working Memory, 4 = Processing Speed.

Figure 5

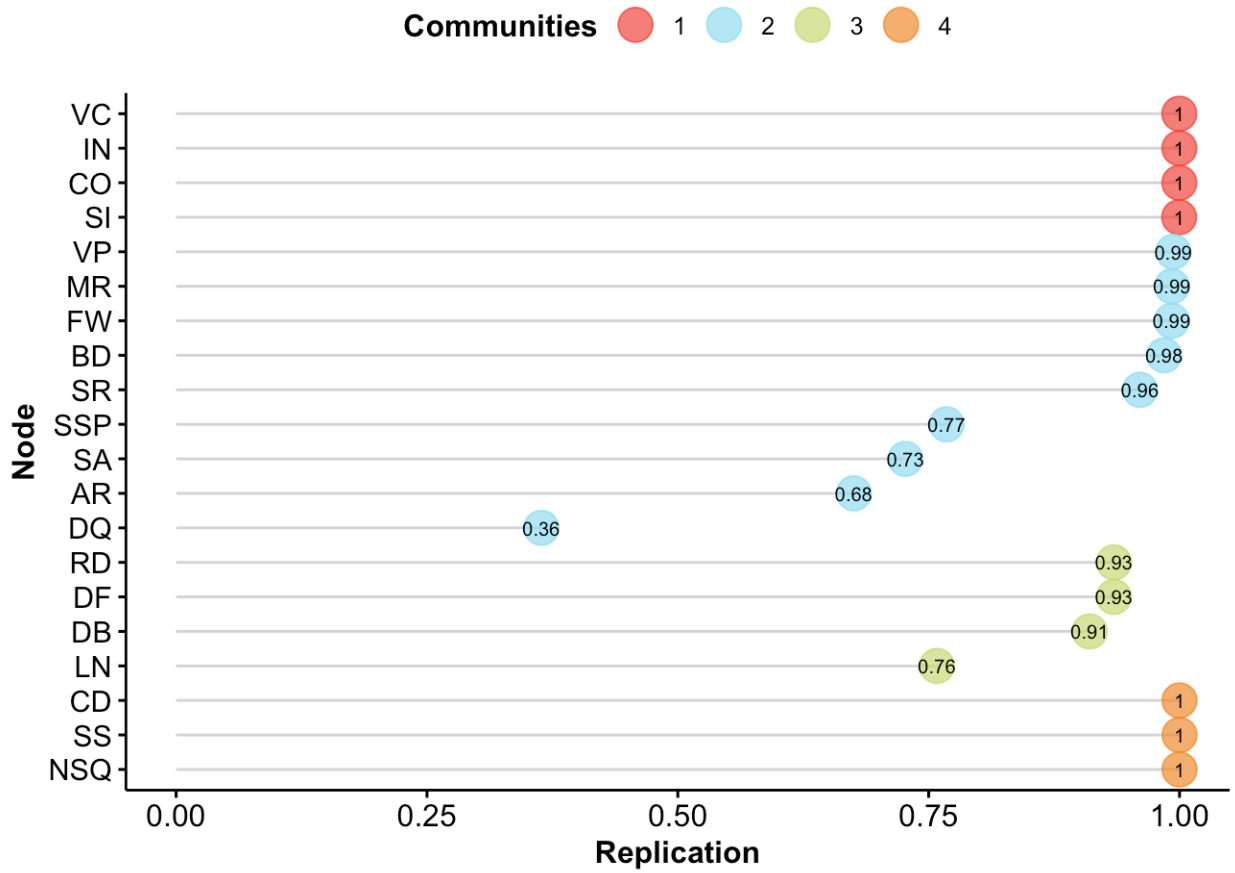
Typical Network Structure of All WAIS-5 Subtests



Note. Zero values have been omitted for table clarity. SI = Similarities, VC = Vocabulary, IN = Information, CO = Comprehension, BD = Block Design, VP = Visual Puzzles, MR = Matrix Reasoning, FW = Figure Weights, AR = Arithmetic, SR = Set Relations, DQ = Digital Sequencing, RD = Running Digits, DF = Digits Forward, DB = Digits Backward, SSP = Symbol Span, SA = Spatial Addition, LN = Letter-Number Sequencing, CD = Coding, SS = Symbol Search, NSQ = Naming Speed Quantity, 1= Verbal Comprehension, 2 = Perceptual Reasoning, 3= Working Memory, 4 = Processing Speed.

Figure 6

Subtest Assignment Stability Over Replications for All Subtests



Note. Zero values have been omitted for table clarity. SI = Similarities, VC = Vocabulary, IN = Information, CO = Comprehension, BD = Block Design, VP = Visual Puzzles, MR = Matrix Reasoning, FW = Figure Weights, AR = Arithmetic, SR = Set Relations, DQ = Digital Sequencing, RD = Running Digits, DF = Digits Forward, DB = Digits Backward, SSP = Symbol Span, SA = Spatial Addition, LN = Letter-Number Sequencing, CD = Coding, SS = Symbol Search, NSQ = Naming Speed Quantity, 1= Verbal Comprehension, 2 = Perceptual Reasoning, 3= Working Memory, 4 = Processing Speed.