Construct Validity and the O*NET Holistic Rating Scales: Evidence of a Fundamental Lack of Discriminant Validity

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Positive claims regarding the construct validity of the *Occupational Information Network* (O*NET) have been made for years; however, reports of high scale multicollinearity (e.g., LaPolice, Carter, & Johnson, 2008) raise doubts regarding discriminant validity. I factor analyzed four O*NET surveys; because each single-item scale is meant to define a distinct *construct*, evidence of construct validity would be seen in high-dimensionality factor solutions and low communalities. Results revealed a fundamental lack of discriminant validity; instead, findings were consistent with the view that O*NET raters exhibit halo error, and rate based on their global views of the *Data, People,* and *Things* dimensions of Fine's *Functional Job Analysis* theory. Although O*NET's constructs may be *conceptually* distinct in the abstract, raters are decidedly unable to make *empirically* distinct ratings of them using O*NET scales; these findings further question the practice of using single-item holistic rating scales to directly rate hypothetical, unobservable, latent trait constructs.

The *Occupational Information Network* (O*NET) that was developed by the US Department of Labor (DOL) to replace the *Dictionary of Occupational Titles* (DOT) has been in applied use for approximately a decade, and it has been almost twenty years since its development was begun (e.g., APDOT, 1992; Dye & Silver, 1999). In my assessment, O*NET is long overdue with respect to receiving a critical assessment of the degree to which it has succeeded at its mission of replacing the DOT, and providing a high-quality source of occupational information for the nation. O*NET's goals were ambitious; as Hubbard, McCloy, Campbell, Nottingham, Lewis, Rivkin, and Levine (2000) noted,

> "O*NET will be *the most comprehensive standard source of occupational information in the United States*. O*NET will be at the center of an extensive network of occupational information used by a wide range of audiences, from individuals making career decisions, to public agencies and schools making training investment decisions, to *employers making job structure and hiring decisions.* O*NET will also be widely used for *administration of federal programs*" (p. v, emphasis added).

In my assessment, a number of fundamental flaws and severe limitations are present in O*NET, and the origins of many of O*NET's problems can be traced back to design decisions that were made in the early 1990's (e.g., see APDOT, 1992; Dye & Silver, 1999). The most notable of these include (a) reliance on a far-too-abstract title taxonomy (Harvey, 2009a) that rates *occupational units* (OUs), or *clusters* of DOT-level occupations, which both effectively guarantees the presence of a large degree of *aggregation bias* (James, 1982), and fails to describe work at the *occupation* or *job* level of analysis needed by most practitioners; (b) the fact that even though high multiple correlations between O*NET scales and external variables can be produced in job-component validation (JCV) models (although typically, only *after* aggregation to the OU-mean level), such equations may still not exhibit adequate precision for applied use (Harvey, 2009b); (c) a total lack of *common-metric* data describing the moderate-specificity, *verifiable* work activities rated in traditional standardized job analysis surveys (e.g., the *Common-Metric Questionnaire,* or CMQ; Harvey, 1991a; and the more-specific items rated in the *Position Analysis Questionnaire,* or PAQ; McCormick, Jeanneret, & Mecham, 1972); and (d) the consistently poor psychometric quality (and pronounced lack of convergence with ratings collected using the *decomposed-judgment* measurement strategy taken by instruments such as the CMQ and PAQ) for ratings collected using the single-item *holistic judgment* strategy used in O*NET (e.g., Butler & Harvey, 1988; DeNisi & Shaw, 1977; Gibson, Harvey, & Harris, 2007).

Evidence for Construct Validity?

In this study, I examined the construct validity of the single-item tests used to collect ratings in the four major O*NET surveys (i.e., *Abilities; Generalized Work Activities*, or *GWAs; Skills;* and *Knowledges*). In the past, many claims to the effect that the O*NET scales exhibit acceptable construct validity have been advanced (e.g., Fleishman & Mumford, 1991; Fleishman & Reilly, 1992; Fleishman, Wetrogan, Uhlman, & Marshall-Mies, 1995; LaPolice, Carter, & Johnson, 2008; Peterson, Mumford, Borman, Jeanneret, Fleishman, Levin, Campion, Mayfield, Morgeson, Pearlman, Gowing, Lancaster, Silver, & Dye, 2001; Sinclair, Russell, Erdheim, Ingerick, Owens, Peterson, & Pearlman, 2009).

As was described in Harvey (2009a), O*NET's claims of construct validity may be challenged on several levels. First, most of the research studies that have been cited in support of an inference of construct validity for O*NET (e.g., Fleishman & Mumford, 1991; Peterson et al., 2001) reported correlations that were computed between *group mean* profiles formed from relatively large groups of raters who rated the same job (“convergent validity”), or who rated different jobs (“discriminant validity”). Here, the sample size for the correlation is the number of rated traits in the survey, and a correlation indexing the relative degree of profile similarity across those rated traits is computed for each pair of rating-source groups using each group's mean on each item to define the data points.

Unfortunately, the results reported in Harvey (2009a) showed that due to the action of James' (1982) *aggregation bias*, sizable-appearing cross-group correlations can be obtained between group-mean profiles (e.g., in the .70's, .80's, and higher) even when *totally random ratings* are made by the raters in each group (hence, *zero* true agreement or ratings quality is present, but the .70 rule-of-thumb for “acceptable” convergence is easily satisfied). Because the real-rater cross-group correlations obtained using O*NET scales are typically of comparable magnitude to (and in some cases, much lower than) the results obtained from random ratings, I do not view the cross-group correlation findings cited by O*NET supporters (e.g., Fleishman & Mumford, 1991; Fleishman et al., 1995; Sinclair et al., 2009) as providing convincing evidence in support of an inference of construct validity. Indeed, the failure of these real-rater results to appreciably exceed the levels of cross-group convergence seen in data having grossly unacceptable known-true levels of data quality (e.g., the random raters in Harvey, 2009a) makes a telling statement regarding the *lack* of adequate convergent validity.

A second line of evidence that is relevant to evaluating past claims of O*NET construct validity can be seen in the degree to which ratings collected using the O*NET scales tend to show a low degree of correlation in ratings of conceptually distinct traits (i.e., discriminant validity). Unfortunately, in this area significant questions can also be raised based on past research. For example, LaPolice et al. (2008) used subsets of O*NET scales as predictors in their JCV analyses. Although strong levels of prediction (*R*s in the .80s) of external criteria were seen, the O*NET scales exhibited a striking degree of multicollinearity (with the median *r* between predictors in one model being .80, with some reaching the low .90s). In my assessment, when scales measuring conceptually different traits exhibit such high degrees of intercorrelation, this fact fundamentally undercuts claims of construct and discriminant validity.

The Present Study

In this study I examined the issue of discriminant validity further, focusing on factor analyses of the O*NET surveys. Although some factor analytic findings were reported by the O*NET's developers (e.g., Costanza, Fleishman, & Marshall-Mies, 1999; Fleishman, Costanza, & Marshall-Mies, 1999; Jeanneret, Borman, Kubisiak, & Hanson, 1999; Mumford, Peterson, & Childs, 1999), they did not report complete factor analytic results (including, particularly, prior estimates of item communality using the common-factor model), they used factor analytic techniques that have been repeatedly questioned in the literature (e.g., principal components analysis with varimax rotation of factors with eigenvalues > 1.0; see Conway & Huffcutt, 2003), and the different studies may have applied different decision criteria during the factor analyses (e.g., regarding the number of factors decision).

In contrast, in this study I used different factoring techniques, including the common-factor model, the scree test to assess dimensionality, and oblique factor rotation. Although I am not claiming that the factor analytic methods used earlier necessarily led to incorrect findings, researchers have long noted (e.g., Conway & Huffcutt, 2003; Tucker, Koopman, & Linn, 1969) that some factor analytic decisions (particularly, using an arbitrary rule-of-thumb to determine the number of factors to retain, and especially *forcing* an orthogonal factor rotation on the results) may tend to produce results that diverge from what one would find when using methods that are (a) more driven by the patterns of results seen in the actual data (e.g., the scree test to identify latent dimensionality) than by the application of rigid rules-of-thumb (e.g., eigenvalues > 1.0); (b) more consistent with Monte Carlo simulations assessing which methods perform best with respect to recovery of known-true factor structures (e.g., Tucker et al., 1969); (c) able to allow correlated factor solutions if they are empirically necessary (i.e., using oblique versus orthogonal rotations); and especially (d) based on a factor analytic model (i.e., the *common-factor analysis* versus *principal component analysis* model) that explicitly focuses on separating *common* variance (i.e., variance due to the action of the underlying latent dimensions of work-activity or worker-traits) from *unique* variance (i.e., variance specific to each rated item).

The fact that in this study the same decision criteria were employed across the factor analyses of all of the four major O*NET surveys (and combinations of surveys) further improves the ability of the present analyses to provide a consistent view of the underlying dimensionality (and degree of discriminant validity) of the item pools rated in O*NET surveys. The main questions addressed here concerned (a) the complexity of the latent dimensionality of the item pool for each O*NET instrument (and the substantive interpretation of the factors themselves), and (b) the magnitude of the item communalities (particularly, the prior communality estimates) seen for the individual O*NET single-item tests rated in each survey.

That is, rather than following the usual approach seen in job analysis – i.e., in which a large number of moderate specificity items are rated, and then work-activity constructs are identified via factor analysis of ratings of those items (e.g., Harvey, 1991b; McCormick et al., 1972) – O*NET *began* the data collection process by directly rating highly abstract work activity and worker-trait *constructs* using single-item scales (e.g., *Decision Making, Explosive Strength, Deductive Reasoning,* and *Critical Thinking*). This approach was taken based on a combination of the pragmatic desire of the O*NET's developers to dramatically reduce data collection costs, and their philosophical view that the DOT's replacement – i.e., *the* national database of occupational information for both public- and private sector organizations – must embody a dramatic shift from methods of occupational analysis based on rating “observable behaviors” to a much more macro and “cognitive analysis” of work (Dye & Silver, 1999, p. 14) in which a much smaller number of abstract work-activity and worker-trait constructs were described.

As has been stressed from the initial phases of O*NET's development (e.g., APDOT, 1992; Dye & Silver, 1999) to the present (Silver, 2009), O*NET's developers viewed the types of data-collection methods used by the DOT, and by the standardized common-metric job analysis surveys that have been in widespread use since the 1950's, to be fundamentally unusable from a cost standpoint (e.g., “DOL suggested that *on-site data collection* used in the DOT methodology *was becoming cost prohibitive*;” Dye & Silver, 1999, p. 14, emphasis added), as well as unacceptable due to being based on the supposedly incorrect and now obsolete views that (a) “a job or occupation as defined by the industrial revolution” is still relevant (Dye & Silver, 1999, p. 12) and (b) occupational information systems should be “focused on observable behaviors” (p. 14). When this fundamental change in occupational analysis philosophy was combined with the belief that only minimal resources should be spent on the nation's primary source of occupational information, the practical implications were significant.

In short, O*NET's developers concluded that O*NET must (a) dramatically reduce the number of “occupations” (actually, OUs, not occupations using the standard definition of the term) in the database from over 12,000 to the current approximately 800 titles; (b) rely on inexpensive surveys of samples of incumbents (or analysts who lack first-hand job experience) to collect data; (c) not rate any of the traditional moderate-specificity work activity content seen in instruments like CMQ; and (d) use the single-item holistic approach to collect direct ratings of each hypothetical work-activity and worker-trait construct. Because the O*NET rating process *starts* at the abstract construct level of analysis, *each rated item* in the four major O*NET surveys studied here is intended to function as a measure of a conceptually distinct latent trait, and to the extent that such single-item tests exhibit construct (discriminant) validity, ratings of *different* traits should exhibit low correlation.

Factor analytic methods can be used to directly assess this construct validity question. Specifically, to the extent that O*NET ratings show acceptable levels of discriminant validity, they should (a) define a relatively high-dimensionality space in the factor solutions (i.e., it should not be possible to explain a sizable portion of the total variance using a small number of factors); and (b) the individual trait ratings should show low communalities, especially prior communalities (which provide the most direct index of the degree of redundancy between the ratings of the different items, one that is not dependent on the number of underlying factors retained).

Here, prior communalities were estimated as the squared multiple correlation (SMC) predicting each item from the remaining items in the pool. Such values provide a very direct index of the degree to which each item measures variance that is not redundant with the ratings of other (conceptually distinct) traits in the survey. Although there is no hard-and-fast rule for what defines an inappropriately large communality, the closer the SMC communality estimates lie to zero, the stronger the evidence of discriminant validity. It is important to note that communalities (abbreviated h^2) are viewed in the common-factor model as representing *squared* quantities (i.e., the proportion of the total variance of a measured item that reflects variance caused by the underlying common factors, in the case of the final communalities); this is significant due to the fact that (a) the square root of a communality lies on the same scale as a correlation coefficient (hence, even h^2 values in the .30's and .40's reflect sizable multiple *R*s predicting the item's variance), and (b) $1 - h^2$ gives the *uniqueness* of an item, which in the present case is the index that operationalizes the *discriminant validity* of an item (i.e., a lack of redundancy with items measuring different constructs is reflected in high uniqueness).

Based on the LaPolice et al. (2008) results showing that high multicollinearity exists among selected O*NET scales, as well as the results of studies showing that single-item holistic ratings exhibit undesirable psychometric properties (e.g., Butler & Harvey, 1988; DeNisi & Shaw, 1977; Gibson et al., 2007; Harvey, Wilson, & Blunt, 1994) and the high final communality values in the low-dimensionality principal component solutions reported by the O*NET's developers (e.g., Costanza et al., 1999; Fleishman et al., 1999; Jeanneret et al., 1999; Mumford et al., 1999), I hypothesized that the factor analyses conducted here would reveal high redundancy between O*NET items, and low-dimensional factor solutions. Operationally, the expected lack of discriminant validity for the O*NET holistic rating scales would be seen in the ability of low-dimensionality factor solutions to account for sizable percentages of the total variance, as well as the presence of high item communalities.

Method

Instruments and Participants

Archival ratings were obtained for 5,862, 6,605, 6,615, and 6,625 rater-title combinations (teams of 5 or more raters that rated a total of from 1,147 to 1,180 *occupational units*, or OUs) using the O*NET *Abilities, Skills, Knowledges,* and *GWAs* surveys, respectively, as part of the initial population of the O*NET database. A total of 1,130 OUs were rated on all four surveys, which formed the sample used for the combined-survey analyses reported below. See Jeanneret and Strong (2003), LaPolice et al. (2008), and the O*NET 98 Data Dictionary technical report (USDOL, 1998; particularly, Appendix D) for more information on the processes used to collect this database and the way in which the OU taxonomy was identified.

Analyses

Exploratory factor analyses were performed using the common factor model, principal axis extraction, SMC estimates of communality, the scree test (combined with examination of multiple solutions for interpretability as needed), and oblique Harris-Kaiser rotation ($p = .5$). For each of the four surveys, analyses were performed twice: once using the rater-level data, and again using the OU-aggregated values. Given the issues noted earlier regarding aggregation bias (Harvey, 2009a), the results from the rater-level data were preferred over the OU-aggregated profiles, in the sense that their results arguably best describe the perceptual processes that were operative among the raters who actually provided the data. Because of the action of aggregation bias, higher communalities would also be expected in the OU-mean profiles than in the original rater-level data.

Additionally, the combined item pools formed from (a) all four surveys, and (b) the work-activity surveys (i.e., *Skills* and *GWAs*) were examined as well to get an alternative overall view of the latent dimensionality of these ratings. Here, because the O*NET analyst raters did not complete all of the different surveys, the factor analyses were only performed at the OU-mean level of analysis. Although the combined item pool from the four surveys was of some interest, primarily because it would be useful in reflecting the degree of item redundancy that exists across the four major surveys (i.e., in a number of cases very similar constructs are rated in the different surveys), the fact that such a combined item pool blurs the job analysis versus worker-specifications distinction (e.g., see Harvey, 1991a) rendered it much less interesting than the combination of the *Skills* and *GWA* surveys, which both clearly describe work behaviors (i.e., the usual focus of a job analysis).

That is, if one subscribes to the view that “skills” are simply the capacity of a worker (based on prior experience, qualifications, training, etc.) to perform a given work activity (e.g., Harvey, 1991a), it is unclear why separate surveys were needed in O*NET to rate “skills” versus “work activities.” This is especially the case in light of the high apparent degree of similarity of items in the two surveys, and the difficulty one has in re-translating *Skills* and *GWA* items back into their original categories. Accordingly, the dimensionality of their combined item pool was of considerable interest.

Results and Discussion

Item Pool Dimensionality and Item Uniqueness

Figures 1-4 present the scree plots of the eigenvalues from the *Abilities, GWAs, Knowledges,* and *Skills* surveys, respectively, showing both the rater-level and OU-mean level of analysis results. Figures 5-8 present the prior and final communality values for the same surveys for the analyses conducted at the rater level of analysis; Figures 9-12 present the corresponding results for the OU-mean level of analysis. An inspection of the scree plot results indicates that – in sharp contrast to the view held by the O*NET's developers that each of the single-item tests contained in these four surveys measures a distinct underlying work-activity or worker-trait construct – the item pools in the four O*NET surveys are dominated by a small number of underlying factors.

For *Abilities,* the Figure 1 scree plot shows that at both the rater and OU-mean level of analysis, two primary underlying dimensions are present, with scree breaks at three or four factors as well. Although the OU aggregation process increased the relative size of the second eigenvalue relative to the rater-level results, a similar pattern of eigenvalues is seen for both. In terms of the percentage of the total *common* variance (i.e., the sum of the prior communality estimates) explained by each unrotated factor, the 2-factor solution explains a very sizable 75% at the OU-mean level of analysis (78% at the rater level), the 3-factor solution explains 83% (85%), and the 4-factor 88% (90%).

Expressed as a percentage of the total variance (i.e., the sum of all item variances, which forms a larger base than the sum of the estimated common-variance components), the eigenvalues for the 4-factor solution explain 72% of the total variance at the OU-level of analysis, and 58% at the rater level. Note that these percentages of total variance for a given dimensionality will tend to be smaller than the results that would be produced from a principal components analysis, given that the factors here were extracted from the *reduced* correlation matrix, not a matrix with unities on the diagonal (in such cases, the same number of factors will tend to explain a higher percentage of the total variance). By way of comparison, in an actual principal components analysis, a 4-factor solution accounts for an even more impressive 91% of the total variance at the OU-mean level of analysis, and 90% at the rater level (a very similar pattern is seen in the scree results for the principal-component eigenvalues in comparison to the common-factor results reported in Figure 1).

Clearly, such results are *not* consistent with the view that these 52 single-item scales represent distinct constructs (at least, not when viewed from the perspective of the raters), as they indicate that very substantial percentages of either total common variance or total ratings variance can be explained using a very small number of factors. This is especially pronounced for the principal-components eigenvalues, where in a 4-factor solution *less than 10% of the total variance* is unaccounted for after the action of only four latent dimensions is taken into account.

Regarding communalities, the results for the *Abilities* survey at the rater level (Figure 5) and OU-level (Figure 9) indicate that – contrary to what should be seen if the O*NET scales define distinct constructs – very high prior communality estimates are present (for rater-level, median = .65, range = .45 – 81; for OU-level, median = .82, range = .59 – .93), as are very strong final communality values (in the 4-factor solution, for rater-level the median = .57, range = .35 – .77; for OU-level, median = .71, range = .42 – .89). Of the two, arguably the prior estimates are the most informative with respect to the question of how *empirically distinct* the ratings of the O*NET single-item tests are. The comparable *final* principal-component communalities at the rater level are median = .60 (range = .39 – .79), and for OU-level, median = .74 (range = .47 – .89), which again illustrate the fact that components-analysis parameters tend to show even higher levels of redundancy.

For the *Abilities* ratings, the above median rater-level prior communality estimate of .65 (i.e., the R^2 predicting the "average" item in this survey from the remaining items) corresponds to a multiple R = .81. Clearly, if on average nearly two-thirds of the variance in an O*NET holistic ability rating is redundant with variance in the ratings of supposedly different traits (and half of the scales show *higher* levels of redundancy), such a finding is fundamentally inconsistent with the conclusion that these single-item tests exhibit good construct validity (in a discriminant validity sense). When viewed at the OU-aggregate level, the fact that the average O*NET *Ability* item shows only 19% unique variance (with an R = .91 predicting it from the remaining supposedly distinct construct ratings) makes a similarly damaging point regarding the profoundly high level of redundancy that exists among the ratings collected using these holistic, single-item tests.

For *GWAs*, the Figure 2 results show that a dominant first factor underlies these supposedly distinct scales (68% of total common variance in OU-mean data, 70% in rater-level), with a smaller break after 3 factors (88% for OU-level, 91% for rater-level). In terms of total variance, the 3-factor solution interpreted below explains 71% at the OU-mean level, and 55% at the rater level. For the principal-components equivalent results, the 3-factor solution explains 72% of the OU-mean total variance, and 70% of the rater-level total variance.

As with the *Abilities* results, *GWA* communality estimates (Figures 6, 10) show that these supposedly distinct scales exhibit considerable redundancy. For the prior estimates, OU-level (median = .85, range = .36-.94) and rater-level results (median = .65, range = .19-.80) show that very sizable percentages of GWA item variance are redundant with ratings of different GWAs (i.e., at the OU-level, on average *85% redundancy*). For the final estimates, OU-level (median = .75, range = .15-.91) and rater-level results (median = .59, range = .13-.79) again show that even with a very low-dimensional solution (3 factors for a pool of 42 supposedly distinct traits) only limited unique variance exists in the GWA ratings.

For *Knowledges*, the Figure 3 results show a somewhat higher degree of complexity than for the other surveys, with breaks at two (59% for OU-level, 69% for rater), five (85%, 96%), and seven (96%, 106%) factors in the scree plot. The 5-factor solution reported below explains 56% of the total variance at OU-mean level, 45% at the rater level. For the corresponding principal-components results, the 5-factor solution explains 61% of the total variance at the OU level, and 52% at the rater level. Communalities were again sizable: for prior estimates, with the OU-level median = .70 (.38 – .84) and rater level median = .50 (.19 – .67); for final estimates, OU-level median = .61 (.09 – .86) and rater-level median = .49 (.06 – .66) values are seen. In the corresponding principal component final communalities, at the OU level the median = .65 (.13 – .86), and at the rater level, median = .56 (.13 – .71).

For *Skills*, the Figure 4 results show a very strong first factor (66% of total common variance in OU-level, 68% in rater-level), with breaks after two (85%, 86%) and three (89%, 91%) factors as well. The 3-factor solution presented below explains 79% of the total variance in the matrix at the OU-mean level (61% at rater level). For the principal component results, the 3-factor solution explains 78% of the OU-mean total variance, and 63% of the rater-level total variance.

Communalities were very high: for prior estimates, at the OU-level median = .88 (.52-.96) and rater level median = .70 (.29-.85), and for final estimates, OU-level median = .81 (.40-.93) and rater-level median = .

65 (.23-.77). Corresponding principal component results for final communalities in the 3-factor solution are median = .81 (.46 – .92) at the OU-level, and median = .66 (.27 – .78) at the rater level.

For the combined item pool for all surveys (which could only be analyzed at the OU-mean level of analysis), Figure 13 presents the scree plot, and Figure 14 presents the communalities. In terms of the scree plot, a clear discontinuity is present after three factors (68% of the total common variance), with smaller breaks after four (72%), six (78%), and eight (83%) factors. The 4-factor solution interpreted below (which was chosen based on its clarity and parsimony) explains 63% of the total variance in the correlation matrix among the 173 items in these four surveys (and 63% in the principal components analysis). In terms of the communalities, the Figure 14 results again indicate that very high prior communality estimates are seen (median = .89, range = .52 to .96), and in the low-dimensionality 4-factor solution chosen for interpretation, sizable final communalities are present (median = .68, range = .01 to .88). For the corresponding principal components results, similar final communality results are seen, with median = .67 (.01 – .88).

Finally, results for the combined *Skills* and *GWAs* surveys are presented in Figures 15 (scree plot) and 16 (communalities). Similar to the above results seen when looking at these two surveys separately, the scree plot reveals a strong break after three factors (82% of common variance, 71% of total variance), with a smaller one after five (88% of common, 77% of total). Prior communalities are substantial, with median = .70 (range = .29 - .85), and even for the 3-factor solution interpreted below, the final communalities (median = .65, range = .23 - .77) are nontrivial. In light of the fact that communalities represent the *percentage* of variance in the item that is redundant with the other items (for the priors) or attributable to the action of the factors (for the final values) and hence non-unique, the fact that only *three* underlying dimensions can account for such sizable proportions of variance in the 88 single-item tests measuring general work-activity constructs – and that such substantial item communalities are seen – is notable. Corresponding results for the principal component analysis are 72% of total variance explained in the 3-factor solution, with final communality values having a median = .66 (.27 – .78).

In sum, the above results indicate that (a) low-dimensional factor solutions can explain substantial proportions of item rating variance in the O*NET surveys, and (b) a very strong degree of redundancy exists among the O*NET items. Taken together, these results document a fundamental *lack* of discriminant validity for these O*NET scales. It is important to stress that in a traditional decomposed-judgment assessment situation (i.e., in which many item-level ratings are collected, but the researcher assumes that they reflect the action of a much smaller number of underlying constructs, as would be the case in the typical personality or ability test), findings such as those reported above would not be viewed as cause for alarm. On the contrary, a test developer would no doubt be very pleased to find that the test items have a high percentage of their variance in common with the underlying factors, and that a high percentage of total variance can be explained using a small, parsimonious number of latent constructs.

However, in the O*NET instruments, precisely the opposite situation is present. That is, each O*NET rating is supposed to function as a *single-item test* that assesses a *separate* underlying trait construct. The fact that very low-dimensional common-factor model solutions are capable of accounting for (at the OU-mean level) an average of *70 percent* of the total variance, and *81 percent* of the common variance (and *76 percent* of total variance in principal components analyses) provides extremely clear evidence that is fundamentally inconsistent with a claim of construct validity for O*NET's assessment surveys.

Substantive Interpretation of Factors

To identify the nature of the underlying constructs to which raters seem to be sensitive when using the O*NET instruments, Tables 1-4 present the rotated primary factor pattern loadings and factor correlations for the *Abilities*, *GWAs*, *Knowledges*, and *Skills* surveys, respectively (rater-level results are reported); Table 5 presents similar results for the item pool from all four surveys, and Table 6 presents results for the combined *Skills* and *GWA*s pool.

For the *Abilities* survey, the results in Table 1 indicate that the 4-factor solution consists of dimensions that I labeled *Cognitive, Gross Physical, Perceptual,* and *Dexterity*. In the corresponding principal component analyses reported by the O*NET's developers for this survey (Fleishman et al., 1999), a 7-factor solution was reported (apparently, based on the use of the eigenvalues > 1.0 rule). In the *Knowledges* domain (Table 3), the 5-

factor dimensions are labeled *Office-Related, Engineering/Production, Social Science, Biological/Health-Related,* and *Infrastructure-Related.* In the corresponding analyses reported by the O*NET's developers (Costanza et al., 1999), a 7-factor solution was reported.

Although the underlying factors seen in the above solutions are easily interpreted, the results for the instruments measuring work-activity constructs (i.e., the usual focus of the job analysis process; e.g., Harvey, 1991a) were of considerably greater interest. As expected, highly similar results are seen for the *GWA* and *Skills* instruments. For *GWAs*, the Table 2 results show a very clear simple-structure solution that is strongly consistent with Sidney Fine's *Functional Job Analysis* (FJA) theory: i.e., *Data, People,* and *Things.* Likewise for *Skills,* the Table 4 results also show factors that bear obvious similarity to Fine's *Data, People,* and *Things* dimensions. Similarly, results for the combined *GWA* and *Skills* pools (Table 6) show a clear simple-structure solution that is immediately recognizable as *Data, People,* and *Things.*

Interestingly, in their principal component analyses the O*NET's authors (Mumford et al., 1999, for *Skills*, and Jeanneret et al., 1999, for *GWAs*) also reported 3-factor solutions for the *GWA* and *Skills* surveys. However, it is significant to note that neither mentioned the obvious similarity of their 3-factor solutions to Fine's well-known FJA worker function taxonomy. That is, in the Jeanneret et al. (1999) chapter, Fine was not even cited; when interpreting their 3-factor solution, these authors chose to name their factors using the much more complex-sounding labels of *Working With Information, Working With and Directing the Activities of Others,* and *Manual and Physical Activities: Performing Repair and Other Physical Work.*

Although Mumford et al. (1999) briefly cited Fine's research in the introduction to their chapter (pp. 50-51) – noting that the *Data, People, Things* dimensions represented a “now-classic taxonomy” – they omitted any mention of this taxonomy when interpreting their 3-factor solution. Instead of using the highly parsimonious (and long-established) *Data, People,* and *Things* constructs to name their factors, they labeled them *Cognitive Skills, Organizational Skills,* and *Technical Skills,* respectively.

Given the fact that Fine's FJA theory predated the O*NET by approximately half a *century*, and by their own acknowledgement FJA's *Data, People, Things* taxonomy has achieved “classic” status (Mumford et al., 1999), it is unclear why both Jeanneret et al. (1999) and Mumford et al. (1999) failed to recognize the presence of *Data, People,* and *Things* factors in their 3-factor solutions. Regardless, I find it notable that in both of the O*NET surveys dealing with work behavior, the latent structure underlying ratings of these 88 one-item tests is highly consistent with Fine's theoretically derived major dimensions of work. Clearly, when rating general work activities/skills, O*NET raters do *not* differentiate to any appreciable degree between these 88 separate traits; instead, their ratings appear to be driven primarily by three macro-level perceptions relating to the information processing, interpersonal, and physical/mechanical aspects of work articulated by FJA's three basic worker functions.

Finally, an inspection of the rotated solution for the combined item pool from all four instruments (Table 5) makes a similar point. Here, the four major factors underlying these 173 supposedly distinct constructs are quite consistent with the overall view of work articulated by FJA, with the addition of an abilities dimension. I labeled these dimensions as *Data, People, Perceptual/Physical Abilities,* and *Things.* Although others may prefer to apply different labels to these overall factors, in my assessment they essentially represent the three major worker functions postulated by FJA, plus a collection of non-cognitive abilities.

Regarding factor correlations, as in past studies (e.g., Harvey, 1987; Harvey, Friedman, Hakel, & Cornelius, 1988), some degree of positive correlation in the *GWA* survey item pool is seen for the factors that define the FJA *Data* and *People* domains. Interestingly, a similar positive factor correlation between *Data* and *People* factors is seen for these factors in the *Skills* domain as well, and also in the combined item pools. Such findings are both easily interpretable on a substantive basis (i.e., in many jobs, many of the decision making activities involve people-based issues such as supervision, resource responsibility, customer interaction, etc.), as well as further evidence of the unacceptability of the practice seen in prior studies (e.g., Costanza et al., 1999; Fleishman et al., 1999; Jeanneret et al., 1999; Mumford et al., 1999) of forcing an orthogonal solution onto data for which an oblique solution is necessary. Indeed, given the fact that the practice of automatically forcing a varimax rotation onto a factor solution has been widely criticized in the literature since the 1960's (e.g., Tucker et al., 1969; see Conway & Huffcutt, 2003, for review), it is somewhat surprising that all of the prior O*NET factor analyses relied on such practices.

Implications for O*NET

In sum, the results reported above paint a disturbing picture with respect to the degree to which the supposedly distinct constructs rated by the single-item tests in the major O*NET surveys lack evidence of discriminant validity. Regarding the big-picture question of how many major dimensions are measured by the combined pool of 173 single-item O*NET tests, the fact that a 4-factor solution explains 72% of the common variance (and 63% of the total variance) strongly implies that the *effective dimensionality* of these surveys is dramatically lower than the number of rated traits, and that the single-item O*NET tests do *not* measure empirically distinct traits.

Likewise, for the two work-activity related surveys (*GWA* and *Skills*), the effective dimensionality of those 88 scales is quite low, and highly consistent with Fine's theoretically derived *Data, People,* and *Things* worker-function constructs. The fact that extremely similar results were obtained from the *Skills* and *GWA* pools when factored separately, and when factored together, further questions the need to use two separate surveys in O*NET to describe work activities. Given the effective isomorphism between the domains of skill and general work activity (i.e., with the most direct definition of a skill simply being formed by taking a given GWA item and prefacing it with the phrase “the capacity to...”), there seems to be little practical or conceptual need to rate such similar domains of content using separate instruments.

Indeed, the above results are consistent with the view (see Harvey, 2009a) that O*NET raters may rely to a considerable degree on a form of *halo error* (e.g., Harvey, 1982) when they rate occupations using the O*NET scales. That is, their ratings of dimensions that arguably represent conceptually distinct work-activity and worker-trait constructs do not even begin to approach the degree of empirical differentiation that one would desire to see (and that would be consistent with an inference of discriminant validity). Instead, O*NET judges seem to be sensitive primarily to a handful of macro-level perceptions of each occupation; specifically, its overall standing on Fine's *Data, People,* and *Things* constructs, and the non-cognitive dimensions from the *Abilities* survey.

Regarding the related issue of how distinct or unique the ratings of each O*NET trait are in practice, the above results for the prior and final communalities indicate that – at an empirical level – the ratings produced by these O*NET raters are *highly* redundant, and lacking in unique variance. Not only does this cause significant practical problems regarding multicollinearity when O*NET scales are used as predictors in JCV regression models (e.g., Jeanneret & Strong, 2003; LaPolice et al., 2008), it also speaks directly to a *lack* of construct validity for the holistic O*NET rating scales themselves.

In my assessment, the root cause of this lack of discriminant/construct validity is not the presence of significant flaws in the conceptual and/or empirically driven taxonomies that led to the identification of these traits (e.g., Costanza et al., 1999; Fleishman et al., 1999; Jeanneret et al., 1999; Mumford et al., 1999). Rather, the high degree of redundancy and lack of unique variance seen for these O*NET scales is much more likely to be a consequence of O*NET's decision to directly rate hypothetical work-activity and worker-trait constructs using single-item *holistic* rating scales (a practice that is highly questionable based on past research; e.g., Butler & Harvey, 1988; DeNisi & Shaw, 1977; Gibson et al., 2007; Harvey et al., 1994; Miller,1956).

Of considerable significance, when one uses the alternative rating approach for measuring abstract work-activity constructs – i.e., a *decomposed judgment* strategy in which numerous more-specific, verifiable work characteristics and activities are rated, then statistically combined to estimate the underlying trait – far lower levels of redundancy are seen between the work dimension scores. For example, Harvey (2004) and Fine, Harvey, and Cronshaw (2004) examined a hierarchical factor solution for the CMQ (Harvey, 1991b), and demonstrated that first-order factor solutions in 78- and 43-factors (i.e., in the latter solution, a very similar degree of specificity vis a vis the traits rated in the *GWA* and *Skills* surveys) exhibited generally low levels of correlation (although it was still possible to identify the higher-level *Data, People,* and *Things* constructs via second-order factor analysis of the first-order factors). Similarly, for the PAQ (McCormick et al., 1972), past research (e.g., Harvey, 1987) has shown that the first-level factors that can be extracted from the ratings of the more-specific PAQ items define an oblique solution, but one that is not characterized by inappropriate levels of redundancy between the latent work activity constructs.

In short, the high levels of multicollinearity seen in O*NET holistic ratings of abstract work-activity constructs are a highly undesirable – and totally *avoidable* – consequence of using single-item holistic judgments to directly rate the traits. By using traditional decomposed-judgment methods, the same underlying constructs can be identified and measured without the highly undesirable degree of multicollinearity and lack of uniqueness that characterizes O*NET data.

Accordingly, with respect to the very serious lack of discriminant validity documented in the O*NET ratings by the results reported above, a very simple and direct solution is available to solve this problem. That is, if O*NET were to abandon the single-item, holistic rating strategy (which was chosen primarily due to an overriding desire to minimize data-collection cost and effort; e.g., see Peterson et al., 2001), and collect data on the same conceptually distinct work-activity dimensions using the decomposed-judgment rating technologies that have been in widespread use in structured job analysis surveys since the late 1950's (see Harvey, 1991a, for background), a measurement system having strong construct validity could easily be produced.

Of course, making such a change would require DOL to invest more time and effort in the data collection process than is now the case. However, the truism that “you get what you pay for” is arguably highly relevant here, and as was noted in greater detail in Harvey (2009a), O*NET as it now stands offers little if any *utility* to the vast majority of personnel and disability-related practitioners who (a) make decisions at the *job* or *occupation* level of analysis (as opposed to the far-more-abstract O*NET OUs), (b) require work to be described in terms of *verifiable*, moderate-specificity descriptors (i.e., the types of items rated in instruments like CMQ), and (c) require ratings that possess demonstrable quality (particularly, ones that are collected using trained, objective, job-knowledgeable raters). Switching from the single-item holistic rating scales now used in O*NET to the well-established decomposed-judgment strategy would allow major progress to be made with respect to addressing the second of these serious limitations in O*NET as it is now implemented.

Adopting the traditional decomposed-judgment rating process would also produce another highly beneficial outcome for O*NET (beyond increasing the discriminant validity of the work dimension scores). That is, because they rate more behaviorally specific work activity items, decomposed-judgment job analysis instruments like CMQ are easier for raters to use (given that far less inference or abstraction is involved in making each rating), and the ratings collected using them can be *independently verified* for accuracy (in contrast to the essentially unverifiable status held by single-item ratings of hypothetical work-activity and worker-trait requirements). Replacing the holistic single-item ratings with a process that rates moderate-specificity, verifiable work characteristics would help address the verifiability limitation noted above as well.

In terms of potential limitations of this study, because O*NET has now essentially replaced the original analyst-collected database analyzed here, it is possible that questions regarding the generalizability of the above results to the current database could be raised. In response, I would first note that past O*NET studies (e.g., Jeanneret & Strong, 2003; LaPolice et al., 2008) made positive statements regarding the degree of care, and extensive rater training, associated with the original data collection process. Second, and of greater importance, it must be stressed that the raters on which O*NET now relies to populate its database consist of untrained, volunteer, effectively anonymous job *incumbents* (for surveys other than *Abilities*), plus for the *Abilities* survey, a new sample of analysts who (like the original analysts studied here) rate without the benefit of having first-hand, on-site experience with the target occupations. This practice is consistent with the overriding design goal of O*NET to dramatically reduce costs, and DOL's view that the DOT's reliance on analysts who had “on-site data collection … was becoming cost prohibitive” (Dye & Silver, 1999, p. 14).

Unfortunately, considerable prior research (e.g., see Harvey, 1991a, for a review) has indicated that ratings obtained from samples of unproctored incumbents (e.g., Green & Stutzman, 1986; Stutzman, 1983; Wilson, Harvey, & Macy, 1990) – as well as raters who lack first-hand job experience (e.g., Friedman & Harvey, 1986; Harvey & Lozada-Larsen, 1988) – are likely to be among the most problematic, both from a general concern regarding ratings quality, and with respect to being able to show strong convergence with the results obtained from highly job-knowledgeable analysts. Accordingly, there is ample reason to hypothesize that any change in data quality that may have been attributable to O*NET's switch from analysts to unsupervised, untrained, instrument-naive incumbents to collect the bulk of its ratings would involve a *decrease* in data quality in general, and even higher prevalence of the halo-type effects observed in this study.

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Table 1. Rotated 4-Factor Solution for *Abilities* (Rater-Level)

	Factor1	Factor2	Factor3	Factor4
Factor1	100 *	-8	27	12
Factor2	-8	100 *	33	34
Factor3	27	33	100 *	27
Factor4	12	34	27	100 *

		Factor1	Factor2	Factor3	Factor4
AL4	Written Expression	85 *	-13	3	-15
AL2	Written Comprehension	85 *	-8	-5	1
AL1	Oral Comprehension	83 *	1	9	-16
AL8	Deductive Reasoning	82 *	2	-4	14
AL3	Oral Expression	79 *	-5	17	-24
AL9	Inductive Reasoning	79 *	0	0	9
AL12	Mathematical Reasoning	76 *	0	-2	6
AL5	Fluency of Ideas	75 *	-2	11	0
AL6	Originality	70 *	4	9	3
AL13	Number Facility	70 *	-4	5	8
AL7	Problem Sensitivity	64 *	5	9	15
AL11	Category Flexibility	60 *	3	4	26
AL10	Information Ordering	60 *	3	-4	42 *
AL15	Speed of Closure	56 *	-9	31	24
AL52	Speech Clarity	53 *	-13	42 *	-29
AL14	Memorization	51 *	2	28	12
AL41	Near Vision	41 *	-17	18	39 *
AL16	Flexibility of Closure	38 *	-3	33	34
AL36	Stamina	-1	81 *	6	-8
AL34	Dynamic Strength	-9	78 *	3	13
AL40	Gross Body Equilibrium	5	74 *	18	-5
AL39	Gross Body Coordination	3	73 *	16	0
AL33	Explosive Strength	-8	71 *	12	17
AL38	Dynamic Flexibility	-7	69 *	8	15
AL32	Static Strength	-9	67 *	7	23
AL35	Trunk Strength	5	65 *	2	13
AL37	Extent Flexibility	-4	59 *	10	30
AL31	Speed of Limb Movement	-8	50 *	24	32
AL26	Multilimb Coordination	-15	48 *	12	36 *
AL50	Sound Localization	0	11	71 *	-2
AL49	Auditory Attention	17	4	69 *	-4
AL45	Peripheral Vision	-3	31	66 *	-3
AL44	Night Vision	4	16	64 *	-3
AL48	Hearing Sensitivity	2	6	63 *	12
AL27	Response Orientation	6	15	59 *	28
AL47	Glare Sensitivity	2	23	57 *	3
AL29	Reaction Time	-6	19	55 *	31
AL42	Far Vision	20	23	53 *	4
AL21	Time Sharing	35	1	53 *	12
AL46	Depth Perception	-12	23	51 *	19
AL51	Speech Recognition	40 *	-7	50 *	-22
AL20	Selective Attention	30	-4	48 *	25
AL28	Rate Control	-6	30	46 *	19
AL18	Spatial Orientation	18	38 *	43 *	6
AL24	Finger Dexterity	2	7	0	78 *
AL22	Arm-Hand Steadiness	-2	17	2	72 *
AL23	Manual Dexterity	-9	26	-3	70 *
AL25	Control Precision	-13	14	15	61 *
AL30	Wrist-Finger Speed	9	11	10	49 *
AL43	Visual Color Discrimination	8	4	27	47 *
AL17	Perceptual Speed	33	-4	30	45 *
AL19	Visualization	31	14	7	42 *

Table 2. Rotated 3-Factor Solution for *GWA*s (Rater-Level)

	Factor1	Factor2	Factor3
Factor1	100 *	45	0
Factor2	45	100 *	-9
Factor3	0	-9	100 *

		Factor1	Factor2	Factor3
gwlvl9	Analyzing Data or Information	84 *	9	-2
gwlvl8	Processing Information	82 *	4	-6
gwlvl2	Identifying Ojects Actions Events	79 *	8	2
gwlvl1	Getting Information	78 *	13	-9
gwlvl12	Updating and Using Relevant Knowledge	78 *	8	14
gwlvl10	Making Decisions and Solving Problems	75 *	23	2
gwlvl25	Documenting or Recording Information	71 *	12	-9
gwlvl26	Interpreting the Meaning of Information for Others	69 *	22	-13
gwlvl7	Evaluating Information to Determine Compliance with Standards	69 *	11	12
gwlvl6	Judging Qualities of Objects Services People	68 *	20	4
gwlvl19	Working with Computers	64 *	7	-5
gwlvl22	Implementing Ideas Programs Systems or Products	60 *	18	21
gwlvl39	Providing Consultation and Advice to Others	58 *	40 *	-9
gwlvl3	Monitoring Processes Materials Surroundings	57 *	9	37
gwlvl5	Estimating Quantifiable Chars of Products Events Information	57 *	20	19
gwlvl27	Communicating with Supervisors Peers or Subordinates	55 *	39	-9
gwlvl11	Thinking Creatively	53 *	26	1
gwlvl15	Organizing Planning Prioritizing Work	52 *	41 *	-2
gwlvl13	Developing Objectives and Strategies	49 *	46 *	-7
gwlvl28	Communicating with People Outside the Organization	43 *	41 *	-33
gwlvl21	Drafting Laying Out and Spec Technical Devices Parts Equip	40 *	4	35
gwlvl35	Developing and Building Teams	9	80 *	9
gwlvl38	Coaching and Developing Others	7	77 *	6
gwlvl37	Guiding Directing and Motivating Subordinates	11	77 *	7
gwlvl41	Staffing Organizational Units	-1	72 *	-1
gwlvl34	Coordinating the Work and Activities of Others	20	71 *	11
gwlvl32	Resolving Conflicts and Negotiating with Others	13	69 *	-16
gwlvl14	Scheduling Work and Activities	25	65 *	-4
gwlvl36	Training and Teaching Others	22	62 *	2
gwlvl29	Establishing and Maintaining Interpersonal Relationships	22	62 *	-21
gwlvl42	Monitoring and Controlling Resources	20	59 *	2
gwlvl31	Selling or Influencing Others	19	58 *	-14
gwlvl40	Performing Administrative Activities	36	50 *	-8
gwlvl30	Assisting and Caring for Others	6	46 *	-8
gwlvl33	Performing For or Working Directly with the Public	4	45 *	-28
gwlvl23	Repairing and Maintaining Mechanical Equipment	-8	2	71 *
gwlvl18	Controlling Machines and Processes	-4	-9	65 *
gwlvl4	Inspecting Equipment Structures Materials	30	2	65 *
gwlvl17	Handling and Moving Objects	-25	-10	52 *
gwlvl24	Repairing and Maintaining Electronic Equipment	21	0	51 *
gwlvl16	Performing General Physical Activities	-36	13	48 *
gwlvl20	Operating Vehicles Mechanized Devices or Equipment	-20	19	31

Table 3. Rotated 5-Factor Solution for *Knowledges* (Rater-Level)

	Factor1	Factor2	Factor3	Factor4	Factor5
Factor1	100 *	1	30	18	29
Factor2	1	100 *	-3	0	13
Factor3	30	-3	100 *	20	23
Factor4	18	0	20	100 *	12
Factor5	29	13	23	12	100 *

		Factor1	Factor2	Factor3	Factor4	Factor5
knlvl1	Administration and Management	77 *	3	-1	9	2
knlvl3	Economics and Accounting	71 *	-7	3	-12	8
knlvl6	Personnel and Human Resources	62 *	-3	5	7	4
knlvl14	Mathematics	59 *	34 *	4	6	2
knlvl24	English Language	54 *	3	18	15	7
knlvl23	Education and Training	50 *	-1	19	26	6
knlvl2	Clerical	49 *	-15	-1	3	13
knlvl4	Sales and Marketing	46 *	-9	20	-9	4
knlvl9	Computers and Electronics	44 *	23	6	-4	9
knlvl32	Communications and Media	43 *	2	27	-3	17
knlvl5	Customer and Personal Service	29 *	-19	8	17	17
knlvl10	Engineering and Technology	4	80 *	-1	1	5
knlvl15	Physics	0	72 *	-3	16	13
knlvl11	Design	15	68 *	10	-14	-6
knlvl13	Mechanical	-25	65 *	-1	-1	15
knlvl12	Building and Construction	-4	54 *	0	-10	7
knlvl7	Production and Processing	9	46 *	-3	-7	-17
knlvl27	History and Archeology	3	10	71 *	2	1
knlvl28	Philosophy	5	2	67 *	12	0
knlvl19	Sociology and Anthropology	17	-8	64 *	12	14
knlvl25	Foreign Language	-1	-9	51 *	6	10
knlvl26	Fine Arts	-5	1	45 *	-11	-16
knlvl17	Biology	4	6	5	74 *	-7
knlvl21	Medicine and dDntistry	-1	-7	6	72 *	9
knlvl22	Therapy and Counseling	11	-18	25	55 *	4
knlvl16	Chemistry	0	39 *	-8	54 *	2
knlvl18	Psychology	36 *	-16	34 *	34 *	12
knlvl8	Food Production	7	4	0	23	-4
knlvl33	Transportation	-1	6	-1	-5	61 *
knlvl29	Public Safety and Security	3	22	-2	16	59 *
knlvl30	Legal, Government and Jurisprudence	33 *	-6	7	7	50 *
knlvl20	Geography	6	8	37 *	-7	49 *
knlvl31	Telecommunications	25	7	9	-7	40 *

Table 4. Rotated 3-Factor Solution for *Skills* (Rater-Level)

	Factor1	Factor2	Factor3
Factor1	100 *	53	12
Factor2	53	100 *	-2
Factor3	12	-2	100 *

		Factor1	Factor2	Factor3
sklvl18	Information Gathering	80 *	12	-10
sklvl8	Active Learning	79 *	15	-3
sklvl19	Information Organization	79 *	7	-9
sklvl20	Synthesis Reorganization	77 *	13	-4
sklvl7	Critical Thinking	75 *	19	-2
sklvl1	Reading Comprehension	75 *	16	-14
sklvl22	Idea Evaluation	72 *	24	1
sklvl5	Mathematics	71 *	-3	13
sklvl21	Idea Generation	71 *	26	-1
sklvl6	Science	67 *	-18	30
sklvl3	Writing	67 *	25	-18
sklvl24	Solution Appraisal	66 *	29	6
sklvl41	Judgment & Decision Making	63 *	31	0
sklvl17	Problem Identification	62 *	25	13
sklvl40	Identification of Key Causes	58 *	36	10
sklvl23	Implementation Planning	57 *	39	0
sklvl10	Monitoring	55 *	29	3
sklvl37	Visioning	55 *	36	11
sklvl39	Identification of Downstream Consequences	54 *	38	15
sklvl25	Operations Analysis	50 *	19	31
sklvl38	Systems Perceptions	49 *	38	20
sklvl9	Learning Strategies	49 *	39	1
sklvl42	Systems Evaluation	47 *	43 *	17
sklvl29	Programming	46 *	-2	13
sklvl11	Social Perceptiveness	14	73 *	-21
sklvl46	Management of Personnel Resources	9	72 *	10
sklvl14	Negotiation	14	70 *	-6
sklvl13	Persuasion	22	67 *	-8
sklvl44	Management of Financial Resources	12	66 *	2
sklvl16	Service Orientation	-2	63 *	-10
sklvl43	Time Management	27	62 *	5
sklvl12	Coordination	24	62 *	3
sklvl15	Instructing	22	59 *	5
sklvl45	Management of Material Resources	14	56 *	25
sklvl4	Speaking	44 *	51 *	-19
sklvl2	Active Listening	43 *	48 *	-20
sklvl34	Equipment Maintenance	-23	4	82 *
sklvl36	Repairing	-25	6	80 *
sklvl35	Troubleshooting	4	5	80 *
sklvl28	Installation	-5	0	73 *
sklvl31	Operation Monitoring	8	-13	72 *
sklvl32	Operation & Control	-1	-7	65 *
sklvl30	Testing	41	-15	64 *
sklvl26	Technology Design	33	0	53 *
sklvl27	Equipment Selection	38	-3	52 *
sklvl33	Product Inspection	33	-2	49 *

Table 5. Rotated 4-Factor Solution for Combined Item Pool (OU-Level)

	Factor1	Factor2	Factor3	Factor4
Factor1	100 *	52	-5	1
Factor2	52	100 *	-4	-12
Factor3	-5	-4	100 *	17
Factor4	1	-12	17	100 *

		Factor1	Factor2	Factor3	Factor4
al15	Speed of Closure	81 *	0	38 *	1
al2	Written Comprehension	79 *	20	-8	-1
gwlvl19	Working with Computers	78 *	3	-20	2
al4	Written Expression	77 *	24	-6	-12
gwlvl8	Processing Information	77 *	19	-21	3
sklvl1	Reading Comprehension	76 *	24	-14	-6
al9	Inductive Reasoning	76 *	21	10	12
al41	Near Vision	75 *	-20	21	1
gwlvl25	Documenting or Recording Information	74 *	17	-12	-6
gwlvl9	Analyzing Data or Information	74 *	28	-13	9
gwlvl12	Updating and Using Relevant Knowledge	73 *	24	-8	22
gwlvl2	Identifying Ojects Actions Events	73 *	26	-7	7
knlvl9	Computers and Electronics	72 *	-8	-9	12
sklvl19	Information Organization	72 *	26	-16	-3
al8	Deductive Reasoning	72 *	27	4	21
sklvl18	Information Gathering	71 *	31	-14	0
gwlvl1	Getting Information	70 *	34	-10	3
sklvl3	Writing	70 *	30	-13	-14
gwlvl26	Interpreting the Meaning of Information for Others	70 *	28	-12	-10
al16	Flexibility of Closure	69 *	-14	49 *	13
al13	Number Facility	67 *	16	-2	16
gwlvl7	Evaluating Information to Determine Compliance with Standards	67 *	25	-11	16
sklvl20	Synthesis Reorganization	67 *	34	-14	3
al11	Category Flexibility	67 *	4	22	10
knlvl24	English Language	66 *	26	-6	-19
al10	Information Ordering	66 *	2	22	35
al12	Mathematical Reasoning	66 *	21	-6	17
al1	Oral Comprehension	66 *	33	4	-17
sklvl8	Active Learning	65 *	38 *	-9	8
sklvl6	Science	65 *	-2	-2	48 *
al14	Memorization	64 *	8	40 *	-17
sklvl7	Critical Thinking	63 *	41 *	-4	5
al17	Perceptual Speed	61 *	-24	51 *	8
al3	Oral Expression	61 *	39 *	10	-23
knlvl14	Mathematics	61 *	21	-20	25
sklvl29	Programming	61 *	0	-15	22
sklvl5	Mathematics	60 *	21	-25	35
gwlvl10	Making Decisions and Solving Problems	60 *	45 *	-8	10
al7	Problem Sensitivity	59 *	30	22	17
gwlvl6	Judging Qualities of Objects Services People	59 *	38 *	-7	3
al5	Fluency of Ideas	57 *	41 *	7	1
sklvl17	Problem Identification	56 *	43 *	-2	14
sklvl2	Active Listening	55 *	41 *	1	-31
gwlvl3	Monitoring Processes Materials Surroundings	54 *	23	16	33
gwlvl39	Providing Consultation and Advice to Others	53 *	51 *	-11	-3
sklvl24	Solution Appraisal	52 *	52 *	-5	13
sklvl4	Speaking	51 *	49 *	1	-26
al52	Speech Clarity	51 *	39 *	25	-33
al6	Originality	48 *	41 *	11	6
gwlvl22	Implementing Ideas Programs Systems or Products	47 *	44 *	-7	32
knlvl2	Clerical	46 *	6	-9	-37 *
gwlvl28	Communicating with People Outside the Organization	45 *	44 *	-4	-35
gwlvl11	Thinking Creatively	45 *	39 *	-13	10
knlvl32	Communications and Media	45 *	29	1	-27
knlvl17	Biology	39 *	5	11	-3
knlvl30	Legal, Government and Jurisprudence	37 *	32	18	-27
knlvl31	Telecommunications	35	11	16	-8
knlvl27	History and Archeology	33	10	5	-14
knlvl28	Philosophy	31	18	13	-26
knlvl21	Medicine and dDntistry	29	6	25	-17
gwlvl16	Performing General Physical Activities	-60 *	20	46 *	25
sklvl46	Management of Personnel Resources	3	87 *	4	6
gwlvl37	Guiding Directing and Motivating Subordinates	1	86 *	1	9
gwlvl35	Developing and Building Teams	5	84 *	5	3
gwlvl34	Coordinating the Work and Activities of Others	11	81 *	8	6
gwlvl41	Staffing Organizational Units	-12	81 *	-1	-1
knlvl1	Administration and Management	18	80 *	-9	-2
sklvl43	Time Management	17	80 *	0	-2
gwlvl14	Scheduling Work and Activities	14	80 *	-3	-6
knlvl6	Personnel and Human Resources	-3	78 *	1	-6
sklvl12	Coordination	16	77 *	14	-5
gwlvl38	Coaching and Developing Others	7	77 *	4	-7
sklvl44	Management of Financial Resources	6	77 *	-14	-4
sklvl45	Management of Material Resources	10	76 *	7	23
sklvl14	Negotiation	17	72 *	-1	-17
gwlvl42	Monitoring and Controlling Resources	9	72 *	-5	-3
gwlvl32	Resolving Conflicts and Negotiating with Others	11	69 *	3	-29
sklvl23	Implementation Planning	36	69 *	-8	7
gwlvl13	Developing Objectives and Strategies	36	66 *	-12	3
gwlvl15	Organizing Planning Prioritizing Work	40 *	63 *	-7	2
sklvl15	Instructing	26	63 *	11	-7
sklvl13	Persuasion	31	63 *	3	-23

sklvl37	Visioning	40 *	61 *	-6	16
gwlvl36	Training and Teaching Others	24	61 *	3	-9
sklvl42	Systems Evaluation	41 *	60 *	-4	17
knlvl23	Education and Training	25	60 *	9	-11
sklvl40	Identification of Key Causes	43 *	60 *	-2	10
gwlvl29	Establishing and Maintaining Interpersonal Relationships	28	59 *	4	-37 *
sklvl39	Identification of Downstream Consequences	43 *	59 *	-2	16
gwlvl31	Selling or Influencing Others	17	59 *	-3	-26
sklvl11	Social Perceptiveness	25	58 *	9	-45 *
sklvl21	Idea Generation	48 *	56 *	-10	8
sklvl22	Idea Evaluation	49 *	56 *	-9	10
knlvl3	Economics and Accounting	15	55 *	-17	-16
sklvl41	Judgment & Decision Making	48 *	55 *	-3	6
sklvl38	Systems Perceptions	45 *	55 *	8	15
sklvl9	Learning Strategies	41 *	54 *	2	-3
gwlvl40	Performing Administrative Activities	35	54 *	-11	-17
gwlvl27	Communicating with Supervisors Peers or Subordinates	51 *	52 *	-5	-6
sklvl10	Monitoring	49 *	51 *	2	-1
knlvl4	Sales and Marketing	-3	50 *	-4	-23
gwlvl5	Estimating Quantifiable Chars of Products Events Information	42 *	50 *	-6	28
knlvl18	Psychology	25	49 *	16	-39 *
knlvl8	Food Production	-2	18	3	2
al30	Wrist-Finger Speed	18	-40 *	33	13
al45	Peripheral Vision	-1	3	89 *	-9
al27	Response Orientation	15	-11	84 *	-1
al29	Reaction Time	6	-19	81 *	9
al18	Spatial Orientation	2	15	78 *	5
al50	Sound Localization	17	-3	76 *	-5
al42	Far Vision	18	20	76 *	-7
al31	Speed of Limb Movement	-25	-14	74 *	15
al44	Night Vision	18	3	74 *	-15
al47	Glare Sensitivity	8	-1	74 *	-3
al46	Depth Perception	-9	-7	74 *	22
al40	Gross Body Equilibrium	-26	8	73 *	15
al28	Rate Control	-5	-14	72 *	12
al39	Gross Body Coordination	-33	10	69 *	11
al26	Multilimb Coordination	-29	-11	67 *	31
al49	Auditory Attention	32	6	67 *	-20
al33	Explosive Strength	-39 *	2	66 *	29
al36	Stamina	-44 *	13	66 *	11
al32	Static Strength	-45 *	2	63 *	25
al21	Time Sharing	38 *	25	63 *	-15
al37	Extent Flexibility	-34	-7	63 *	30
al48	Hearing Sensitivity	19	-8	63 *	4
al34	Dynamic Strength	-46 *	1	62 *	26
al38	Dynamic Flexibility	-38 *	-4	62 *	22
al35	Trunk Strength	-33	5	61 *	18
al20	Selective Attention	56 *	-4	59 *	-5
gwlvl20	Operating Vehicles Mechanized Devices or Equipment	-25	15	51 *	0
knlvl29	Public Safety and Security	15	24	50 *	6
al23	Manual Dexterity	-11	-28	46 *	45 *
knlvl33	Transportation	-4	19	44 *	-13
al43	Visual Color Discrimination	27	-25	40 *	27
al22	Arm-Hand Steadiness	2	-34	39 *	38 *
knlvl20	Geography	23	17	26	-22
knlvl10	Engineering and Technology	16	5	9	79 *
sklvl27	Equipment Selection	21	23	2	75 *
knlvl13	Mechanical	-23	0	28	73 *
sklvl35	Troubleshooting	9	1	22	73 *
gwlvl4	Inspecting Equipment Structures Materials	18	10	14	72 *
sklvl28	Installation	-9	1	14	72 *
sklvl30	Testing	44 *	-7	6	72 *
sklvl33	Product Inspection	24	12	-6	69 *
sklvl26	Technology Design	24	13	-3	68 *
knlvl11	Design	16	9	-9	66 *
knlvl15	Physics	23	0	15	66 *
gwlvl21	Drafting Laying Out and Spec Technical Devices Parts Equip	30	20	-10	64 *
sklvl34	Equipment Maintenance	-19	-8	28	64 *
sklvl36	Repairing	-21	-7	25	62 *
gwlvl18	Controlling Machines and Processes	-15	-21	11	62 *
sklvl31	Operation Monitoring	16	-23	23	62 *
knlvl7	Production and Processing	-11	6	-11	61 *
gwlvl23	Repairing and Maintaining Mechanical Equipment	-22	-4	25	60 *
knlvl12	Building and Construction	-29	24	9	56 *
al19	Visualization	19	10	28	54 *
sklvl32	Operation & Control	3	-19	26	53 *
al25	Control Precision	3	-31	43 *	53 *
sklvl25	Operations Analysis	33	50 *	-22	51 *
gwlvl24	Repairing and Maintaining Electronic Equipment	25	-13	11	46 *
gwlvl17	Handling and Moving Objects	-40 *	-21	21	43 *
al24	Finger Dexterity	21	-42 *	31	42 *
knlvl16	Chemistry	31	-4	8	32
knlvl26	Fine Arts	-4	3	0	-7
knlvl25	Foreign Language	23	9	15	-32
knlvl22	Therapy and Counseling	20	28	16	-33
knlvl19	Sociology and Anthropology	33	30	14	-39 *
al51	Speech Recognition	41 *	30	31	-43 *
gwlvl30	Assisting and Caring for Others	15	29	17	-45 *
knlvl5	Customer and Personal Service	3	36	14	-45 *
sklvl16	Service Orientation	14	41 *	15	-49 *
gwlvl33	Performing For or Working Directly with the Public	15	34	14	-59 *

Table 6. Rotated 3-Factor Solution for *GWAs* and *Skills* (OU-Level)

	Factor1	Factor2	Factor3
Factor1	100 *	50	0
Factor2	50	100 *	-12
Factor3	0	-12	100 *

		Factor1	Factor2	Factor3
gwlvl8	Processing Information	88 *	4	-9
gwlvl9	Analyzing Data or Information	88 *	11	-1
sklvl18	Information Gathering	86 *	14	-10
sklvl19	Information Organization	85 *	10	-14
sklvl20	Synthesis Reorganization	84 *	14	-9
sklvl8	Active Learning	83 *	19	-2
gwlvl12	Updating and Using Relevant Knowledge	83 *	12	17
sklvl1	Reading Comprehension	82 *	16	-12
sklvl5	Mathematics	82 *	-4	17
gwlvl1	Getting Information	82 *	21	-4
gwlvl2	Identifying Ojects Actions Events	81 *	16	2
gwlvl19	Working with Computers	80 *	-3	-4
sklvl7	Critical Thinking	79 *	24	-1
gwlvl26	Interpreting the Meaning of Information for Others	77 *	19	-14
gwlvl25	Documenting or Recording Information	77 *	12	-9
sklvl3	Writing	76 *	22	-18
gwlvl10	Making Decisions and Solving Problems	75 *	29	2
sklvl6	Science	75 *	-16	41
gwlvl7	Evaluating Information to Determine Compliance with Standards	74 *	17	9
sklvl22	Idea Evaluation	71 *	34	0
sklvl29	Programming	71 *	-14	13
gwlvl6	Judging Qualities of Objects Services People	71 *	26	-2
sklvl24	Solution Appraisal	70 *	33	5
sklvl21	Idea Generation	70 *	34	-2
sklvl41	Judgment & Decision Making	67 *	35	0
sklvl17	Problem Identification	67 *	32	14
gwlvl22	Implementing Ideas Programs Systems or Products	66 *	25	23
gwlvl39	Providing Consultation and Advice to Others	64 *	40	-9
sklvl37	Visioning	63 *	39	6
sklvl39	Identification of Downstream Consequences	63 *	39	9
sklvl25	Operations Analysis	62 *	21	34
gwlvl5	Estimating Quantifiable Chars of Products Events Information	62 *	30	21
sklvl40	Identification of Key Causes	61 *	43	6
sklvl42	Systems Evaluation	59 *	43	12
gwlvl11	Thinking Creatively	59 *	23	-2
sklvl10	Monitoring	59 *	41	-3
sklvl38	Systems Perceptions	59 *	40	15
sklvl23	Implementation Planning	58 *	48 *	0
gwlvl27	Communicating with Supervisors Peers or Subordinates	57 *	45 *	-7
sklvl2	Active Listening	56 *	39	-27
gwlvl15	Organizing Planning Prioritizing Work	55 *	50 *	-4
gwlvl13	Developing Objectives and Strategies	55 *	49 *	-6
sklvl4	Speaking	54 *	46 *	-23
gwlvl3	Monitoring Processes Materials Surroundings	53 *	22	42
sklvl9	Learning Strategies	52 *	45 *	-4
gwlvl28	Communicating with People Outside the Organization	47 *	43	-35
gwlvl20	Operating Vehicles Mechanized Devices or Equipment	-36	26	25
gwlvl16	Performing General Physical Activities	-56 *	18	40
gwlvl35	Developing and Building Teams	10	84 *	9
sklvl46	Management of Personnel Resources	11	84 *	10
gwlvl37	Guiding Directing and Motivating Subordinates	9	84 *	11
gwlvl34	Coordinating the Work and Activities of Others	15	82 *	12
gwlvl41	Staffing Organizational Units	-6	82 *	2
gwlvl38	Coaching and Developing Others	9	80 *	1
gwlvl14	Scheduling Work and Activities	20	79 *	-3
gwlvl32	Resolving Conflicts and Negotiating with Others	8	75 *	-22
gwlvl42	Monitoring and Controlling Resources	13	73 *	-1
sklvl12	Coordination	25	71 *	1
sklvl43	Time Management	29	71 *	-1
sklvl45	Management of Material Resources	20	68 *	23
gwlvl29	Establishing and Maintaining Interpersonal Relationships	24	67 *	-28
sklvl44	Management of Financial Resources	21	66 *	-10
sklvl14	Negotiation	28	65 *	-19
sklvl11	Social Perceptiveness	23	64 *	-35
sklvl15	Instructing	29	63 *	1
gwlvl36	Training and Teaching Others	27	62 *	-2
gwlvl31	Selling or Influencing Others	20	59 *	-24
gwlvl40	Performing Administrative Activities	34	58 *	-14

sklvl16	Service Orientation	3	56 *	-32
sklvl13	Persuasion	39	56 *	-23
gwlvl30	Assisting and Caring for Others	4	45 *	-27
sklvl35	Troubleshooting	3	5	88 *
sklvl34	Equipment Maintenance	-31	4	84 *
sklvl36	Repairing	-30	2	80 *
gwlvl4	Inspecting Equipment Structures Materials	20	7	79 *
sklvl28	Installation	-7	-2	79 *
sklvl31	Operation Monitoring	3	-11	79 *
gwlvl23	Repairing and Maintaining Mechanical Equipment	-30	4	77 *
sklvl30	Testing	48 *	-15	75 *
sklvl32	Operation & Control	-13	-4	72 *
sklvl27	Equipment Selection	39	5	69 *
gwlvl18	Controlling Machines and Processes	-19	-17	68 *
sklvl26	Technology Design	40	-3	63 *
sklvl33	Product Inspection	35	-2	62 *
gwlvl24	Repairing and Maintaining Electronic Equipment	13	-3	59 *
gwlvl17	Handling and Moving Objects	-42	-19	48 *
gwlvl21	Drafting Laying Out and Spec Technical Devices Parts Equip	50 *	-4	48 *
gwlvl33	Performing For or Working Directly with the Public	4	48 *	-45 *

Figure 1. Scree plot of eigenvalues of reduced correlation matrix (SMC communality estimates) for the 52 single-item tests contained in the *Abilties* survey. Eigenvalues for OU-mean analysis are shown as squares, with results for rater-level analysis shown as '+'.

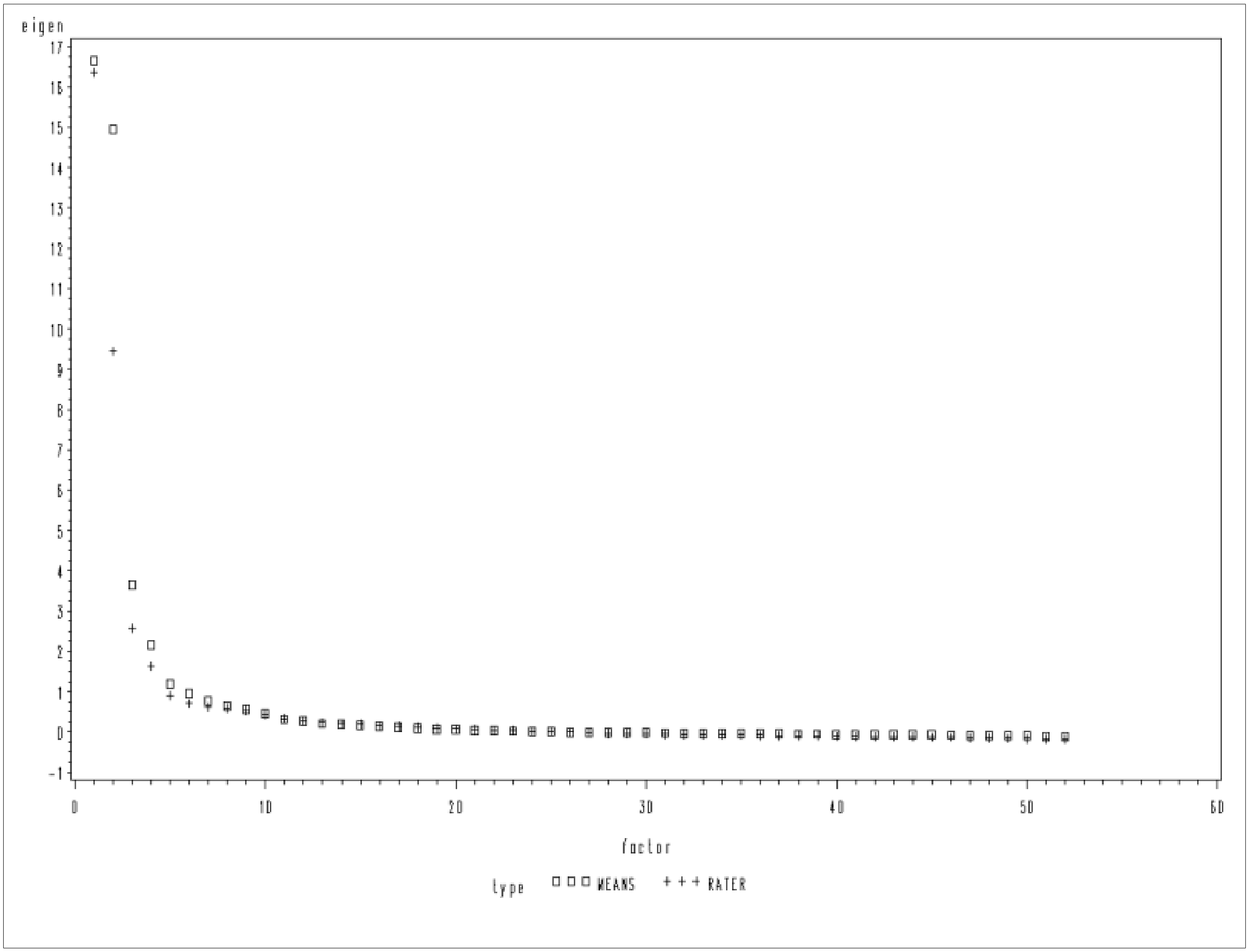


Figure 2. Scree plot of eigenvalues of reduced correlation matrix (SMC communality estimates) for the 42 single-item tests contained in the *GWA* survey. Eigenvalues for OU-mean analysis are shown as squares, with results for rater-level analysis shown as '+'.

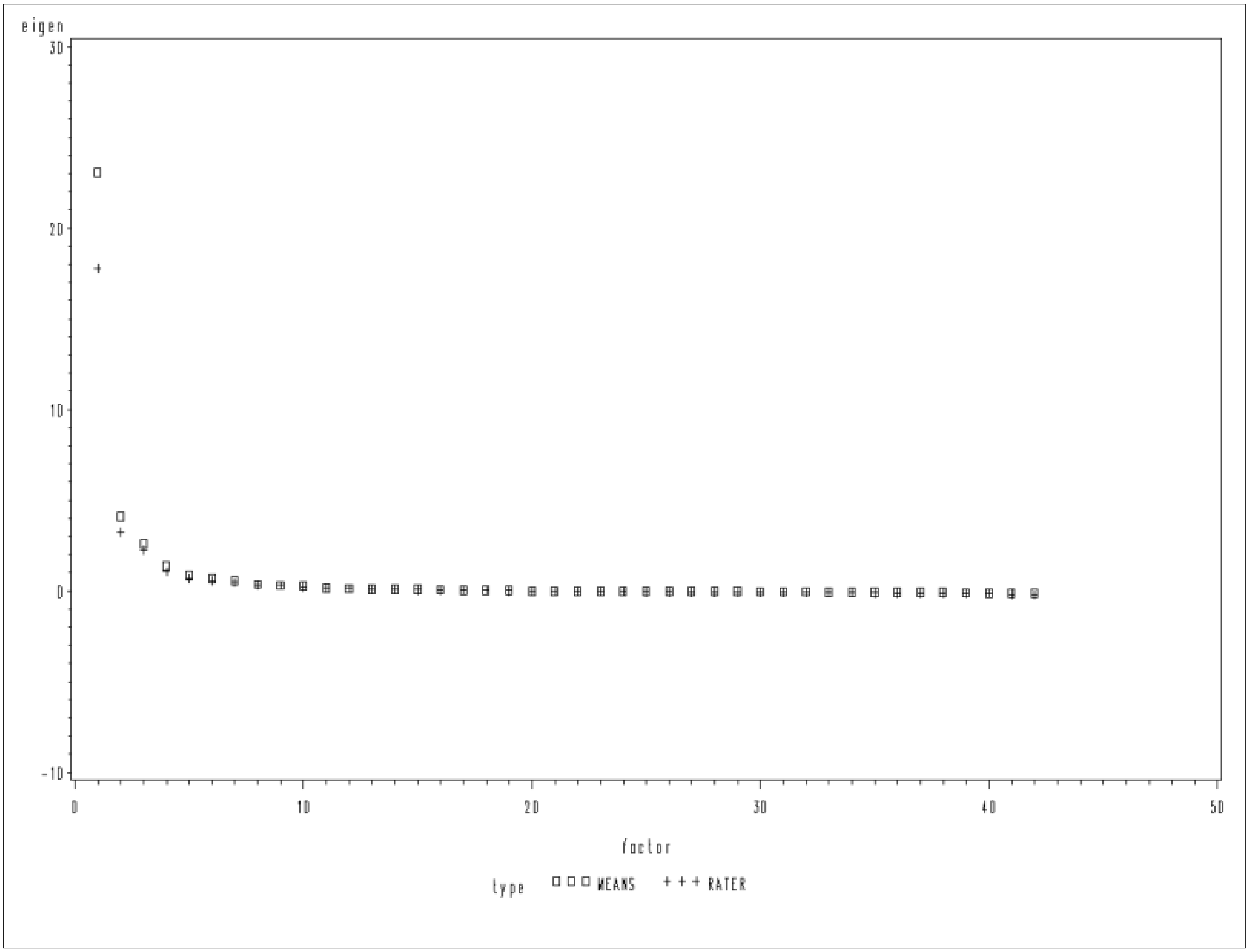


Figure 3. Scree plot of eigenvalues of reduced correlation matrix (SMC communality estimates) for the 33 single-item tests contained in the *Knowledges* survey. Eigenvalues for OU-mean analysis are shown as squares, with results for rater-level analysis shown as '+'.

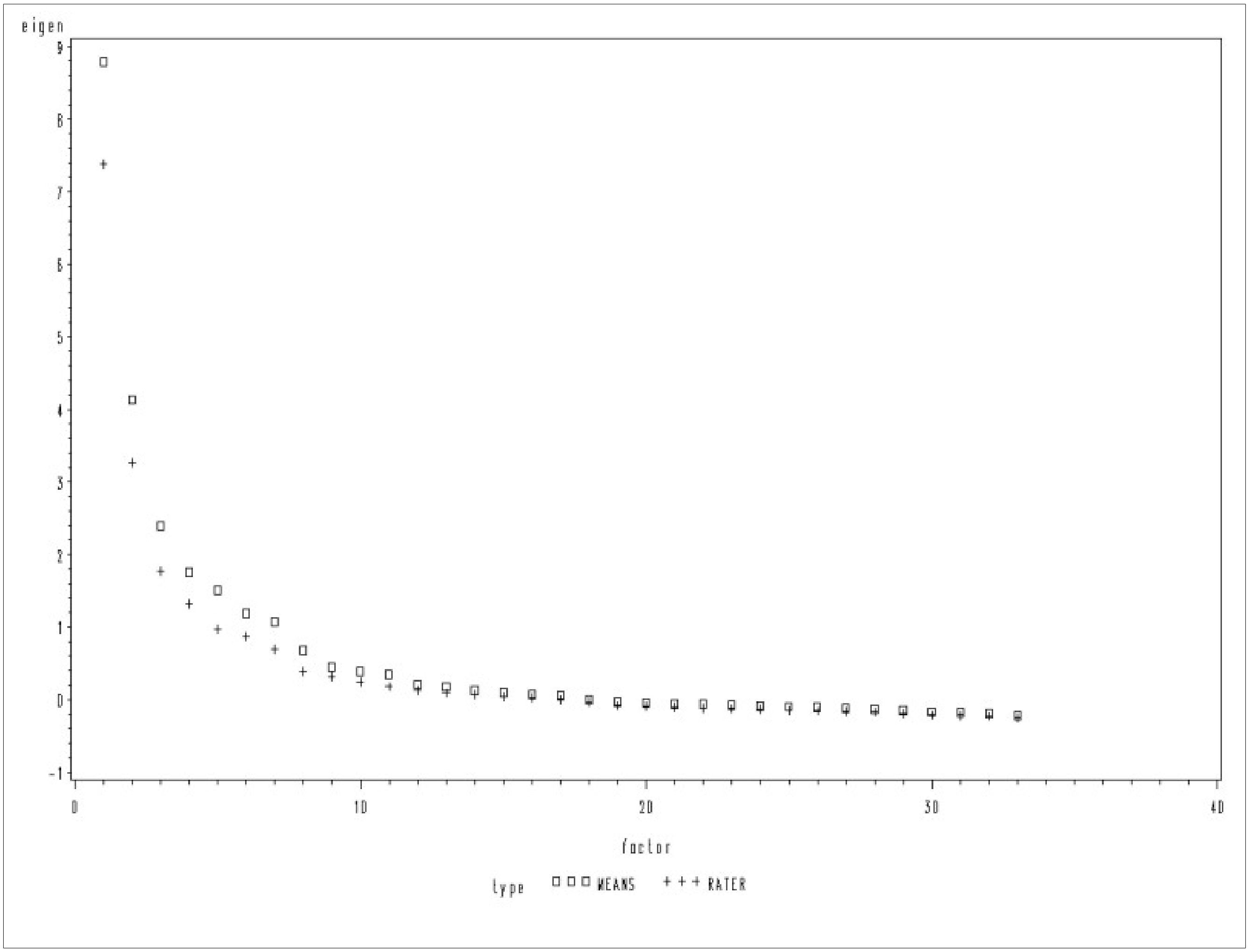


Figure 4. Scree plot of eigenvalues of reduced correlation matrix (SMC communality estimates) for the 33 single-item tests contained in the *Skills* survey. Eigenvalues for OU-mean analysis are shown as squares, with results for rater-level analysis shown as '+'.

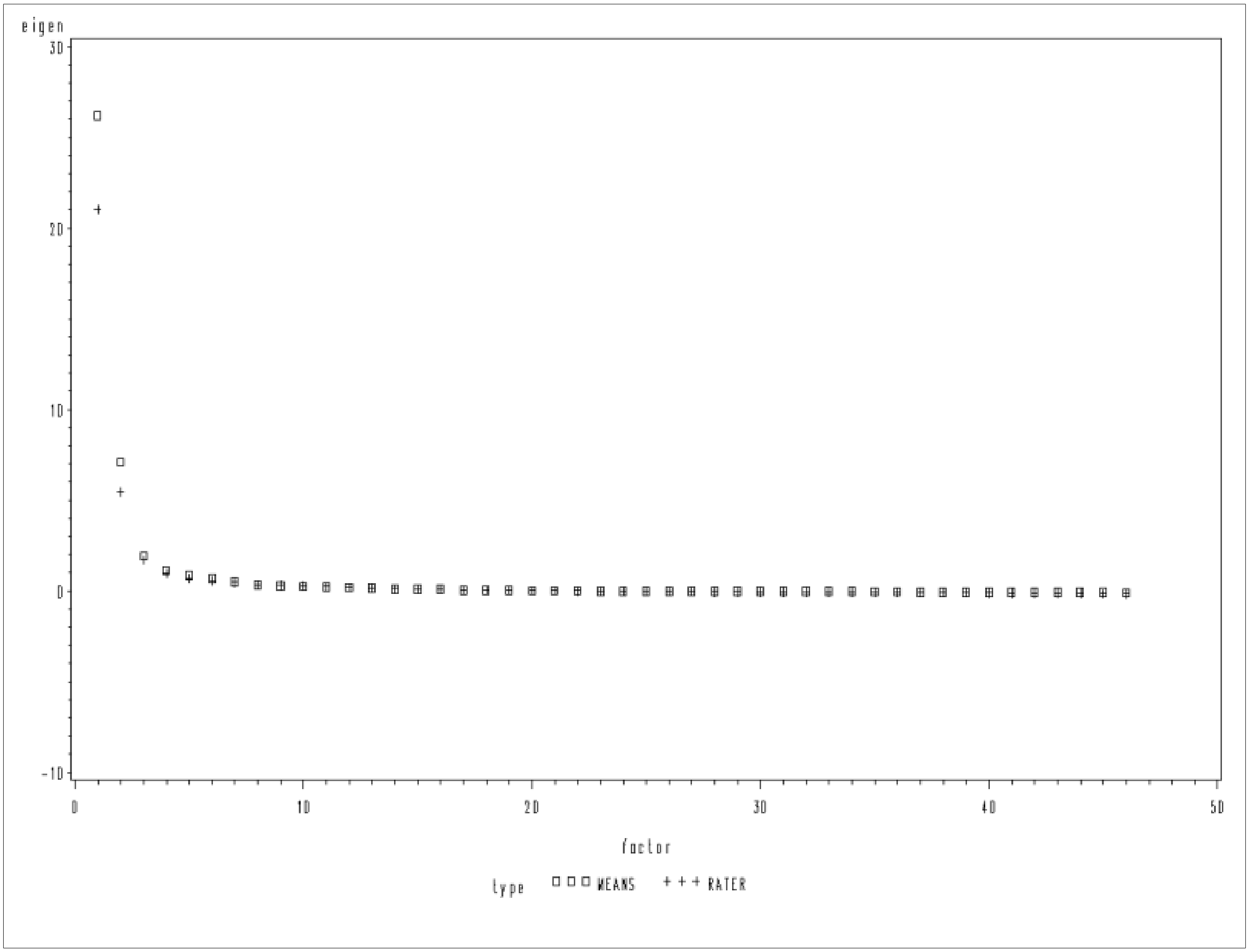


Figure 5. Final communality values for the 4-factor solution (top) and prior (SMC) communality estimates for the *Abilities* survey computed at the rater unit of analysis.

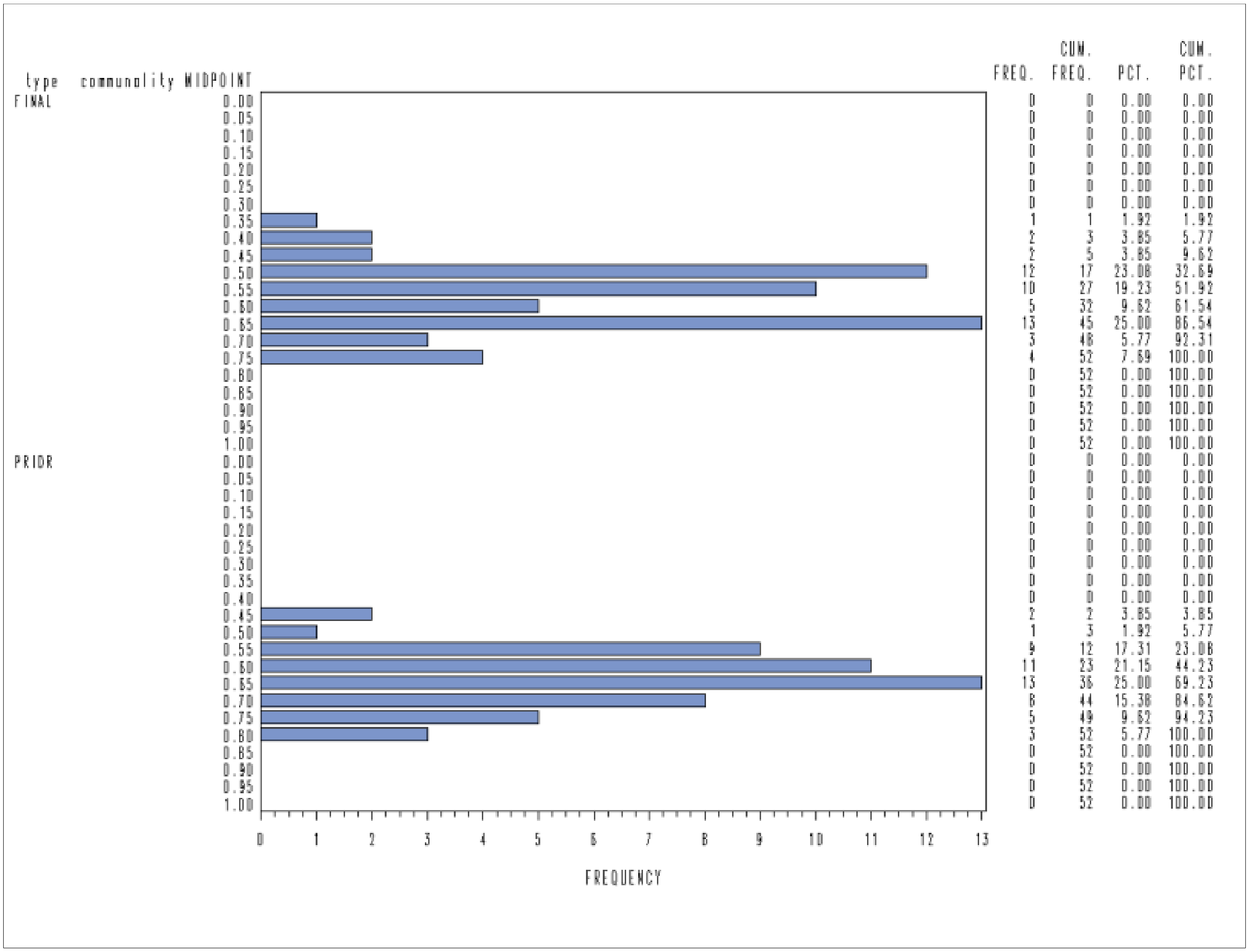


Figure 6. Final communality values for the 4-factor solution (top) and prior (SMC) communality estimates for the *GWAs* survey computed at the rater unit of analysis.

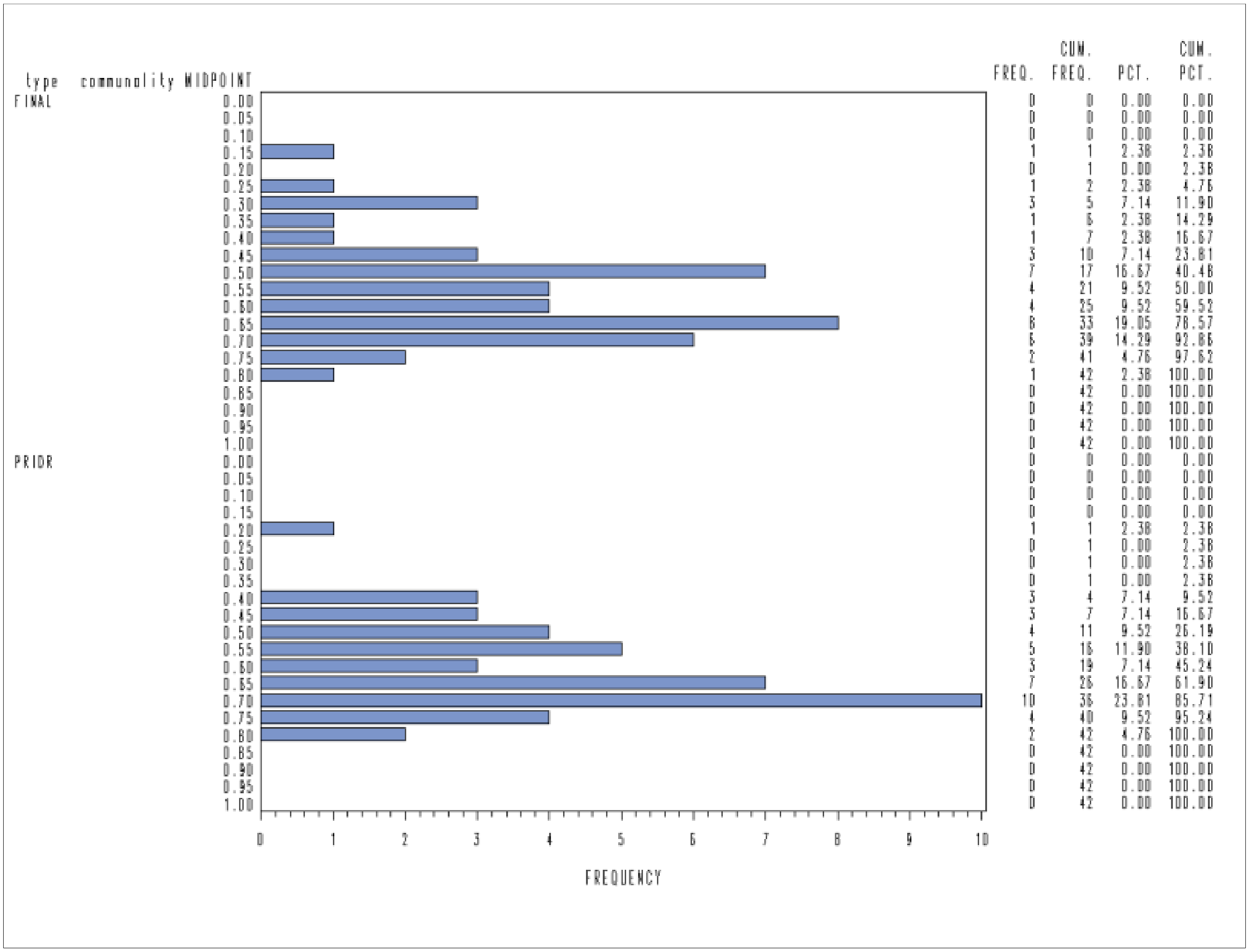


Figure 7. Final communality values for the 5-factor solution (top) and prior (SMC) communality estimates for the *Knowledges* survey computed at the rater unit of analysis.

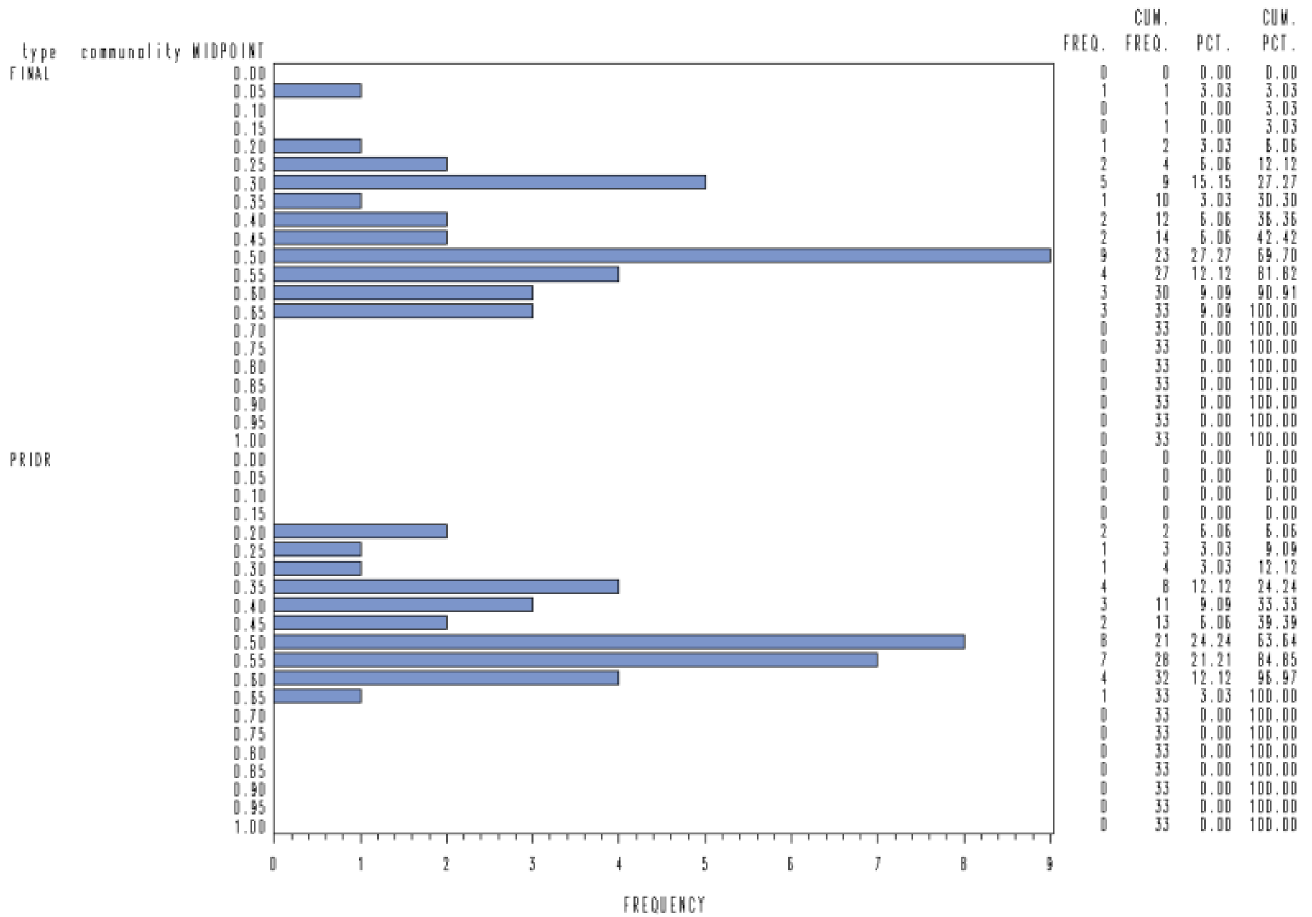


Figure 8. Final communality values for the 3-factor solution (top) and prior (SMC) communality estimates for the *Skills* survey computed at the rater unit of analysis.

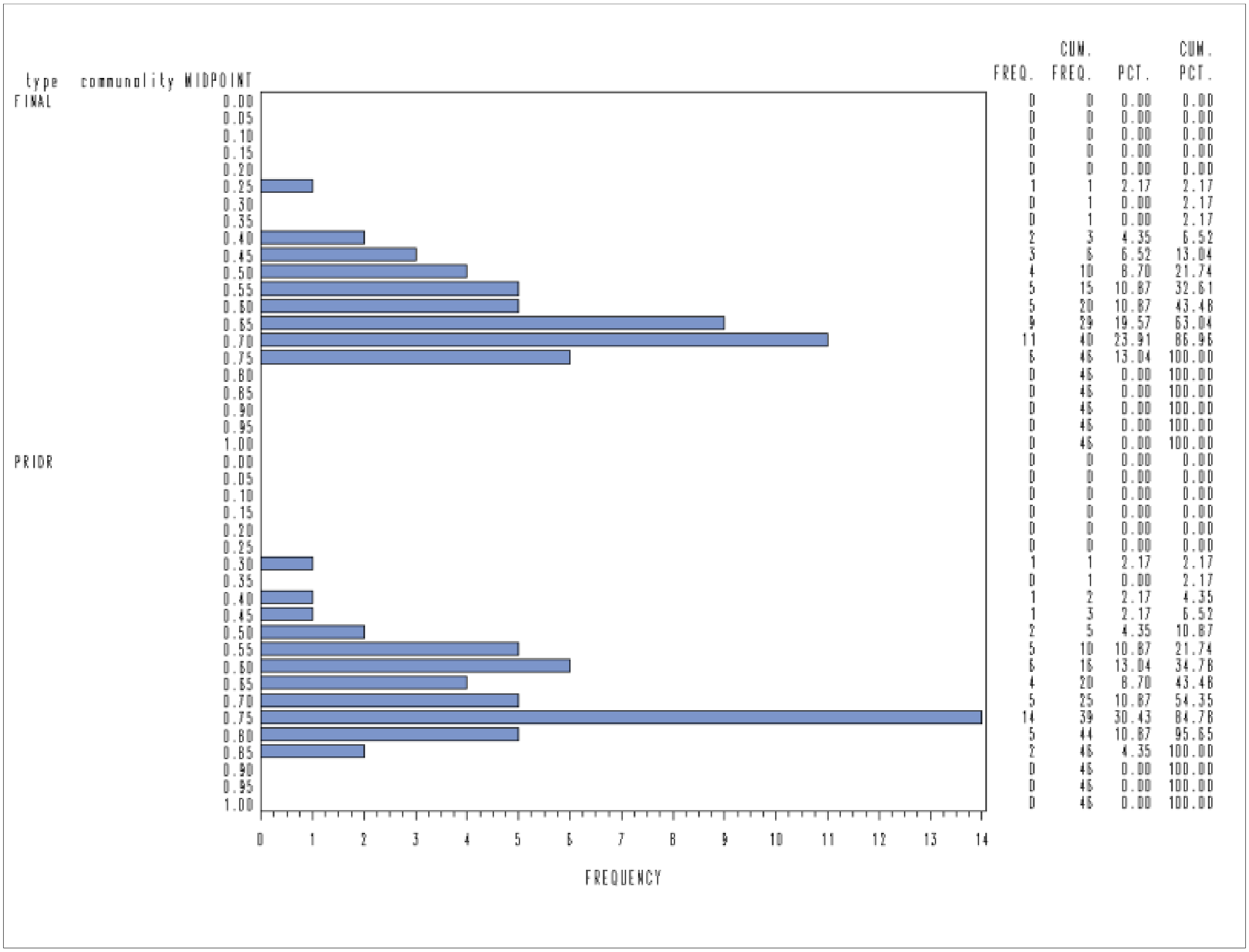


Figure 9. Final communality values for the 4-factor solution (top) and prior (SMC) communality estimates for the *Abilities* survey computed at the OU-mean unit of analysis.

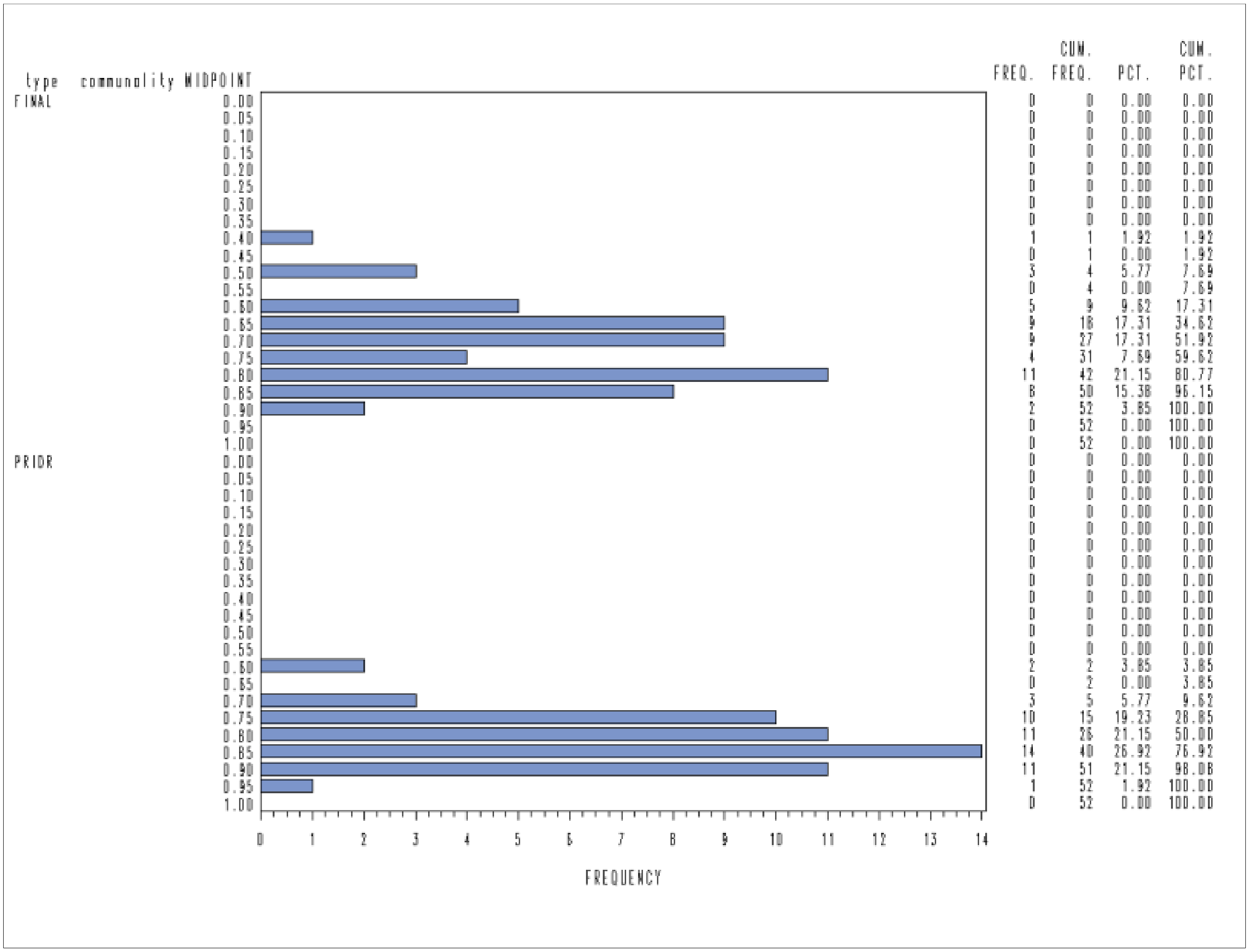


Figure 10. Final communality values for the 3-factor solution (top) and prior (SMC) communality estimates for the *GWAs* survey computed at the OU-mean unit of analysis.

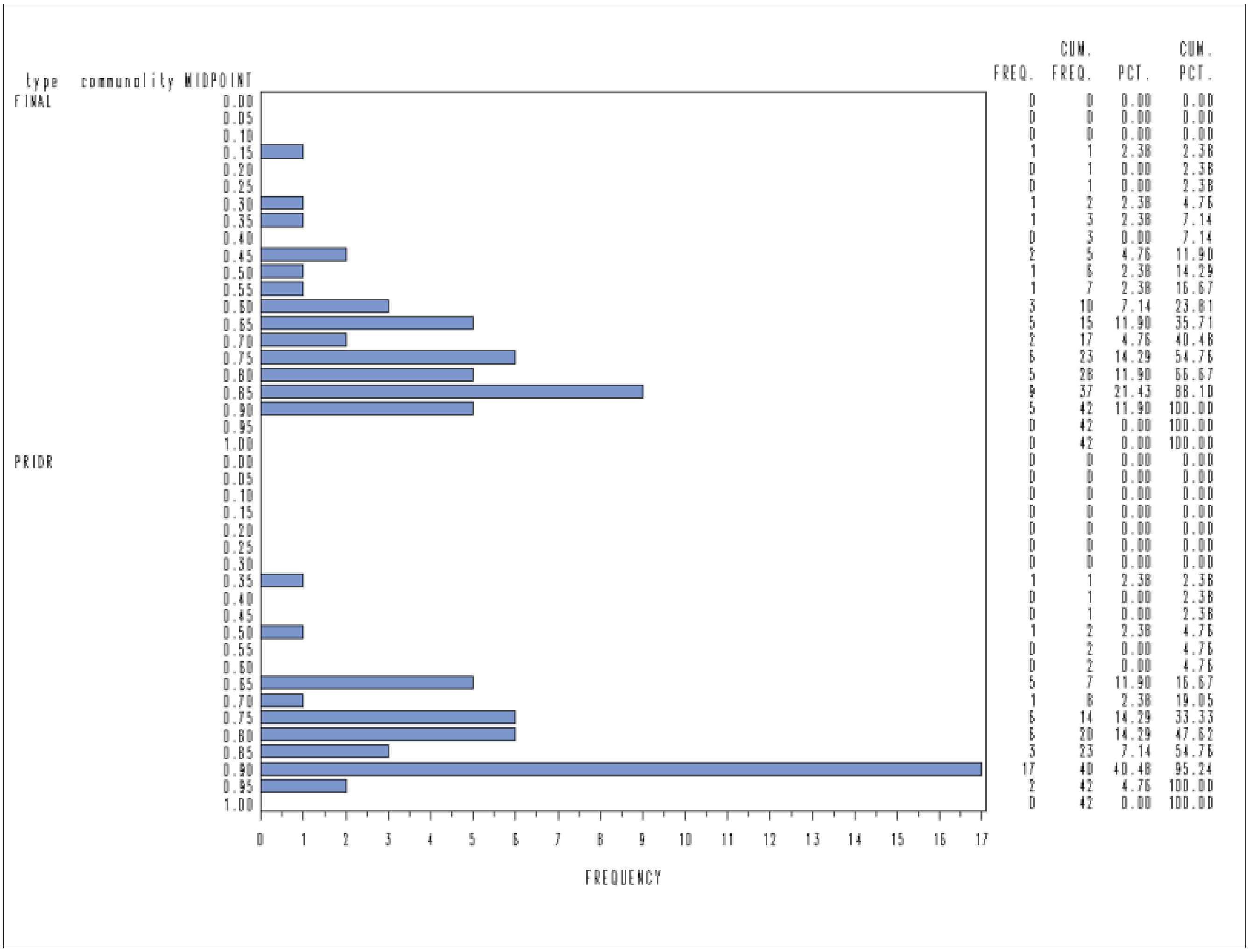


Figure 11. Final communality values for the 5-factor solution (top) and prior (SMC) communality estimates for the *Knowledges* survey computed at the OU-mean unit of analysis.

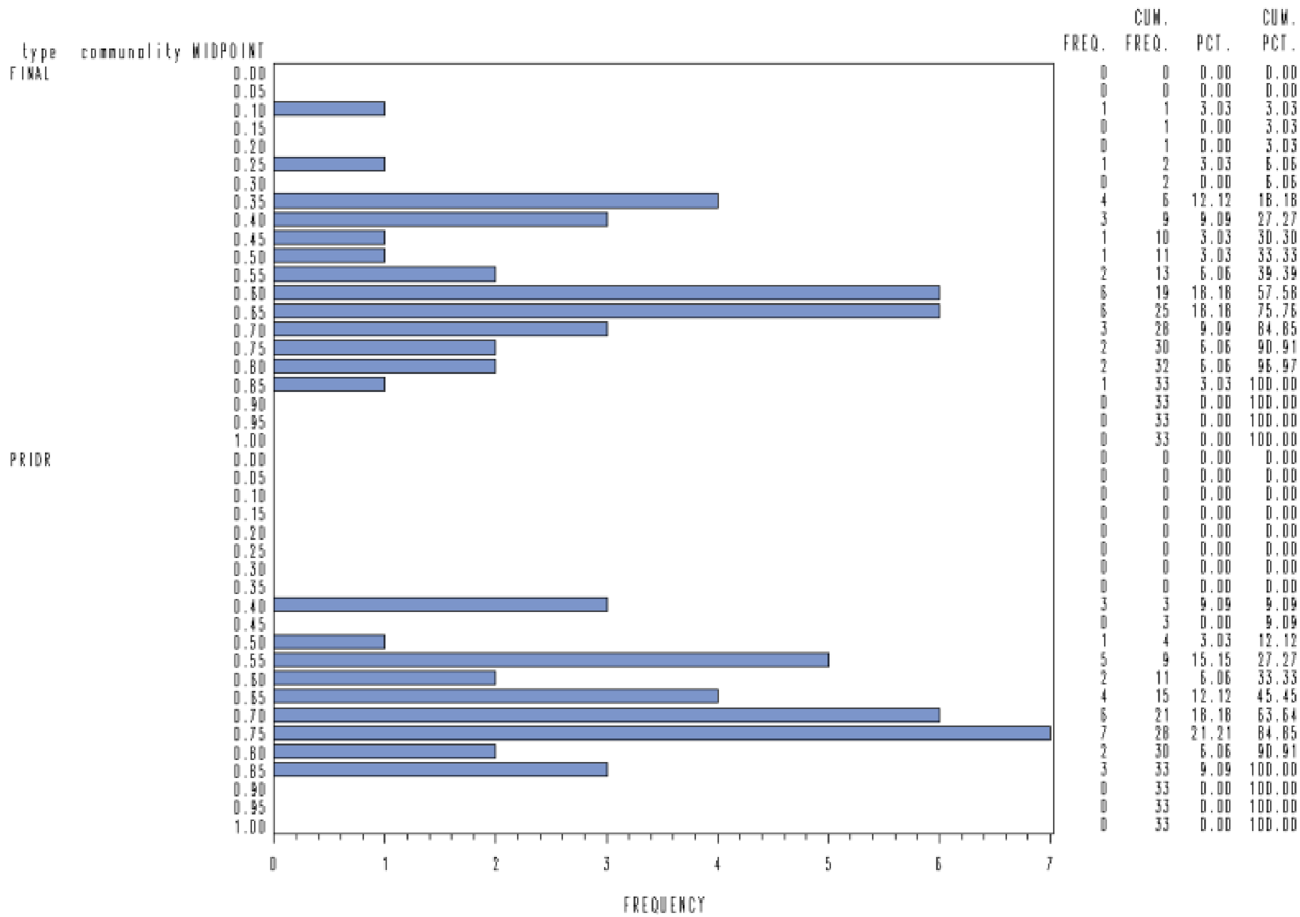


Figure 12. Final communality values for the 3-factor solution (top) and prior (SMC) communality estimates for the *Skills* survey computed at the OU-mean unit of analysis.

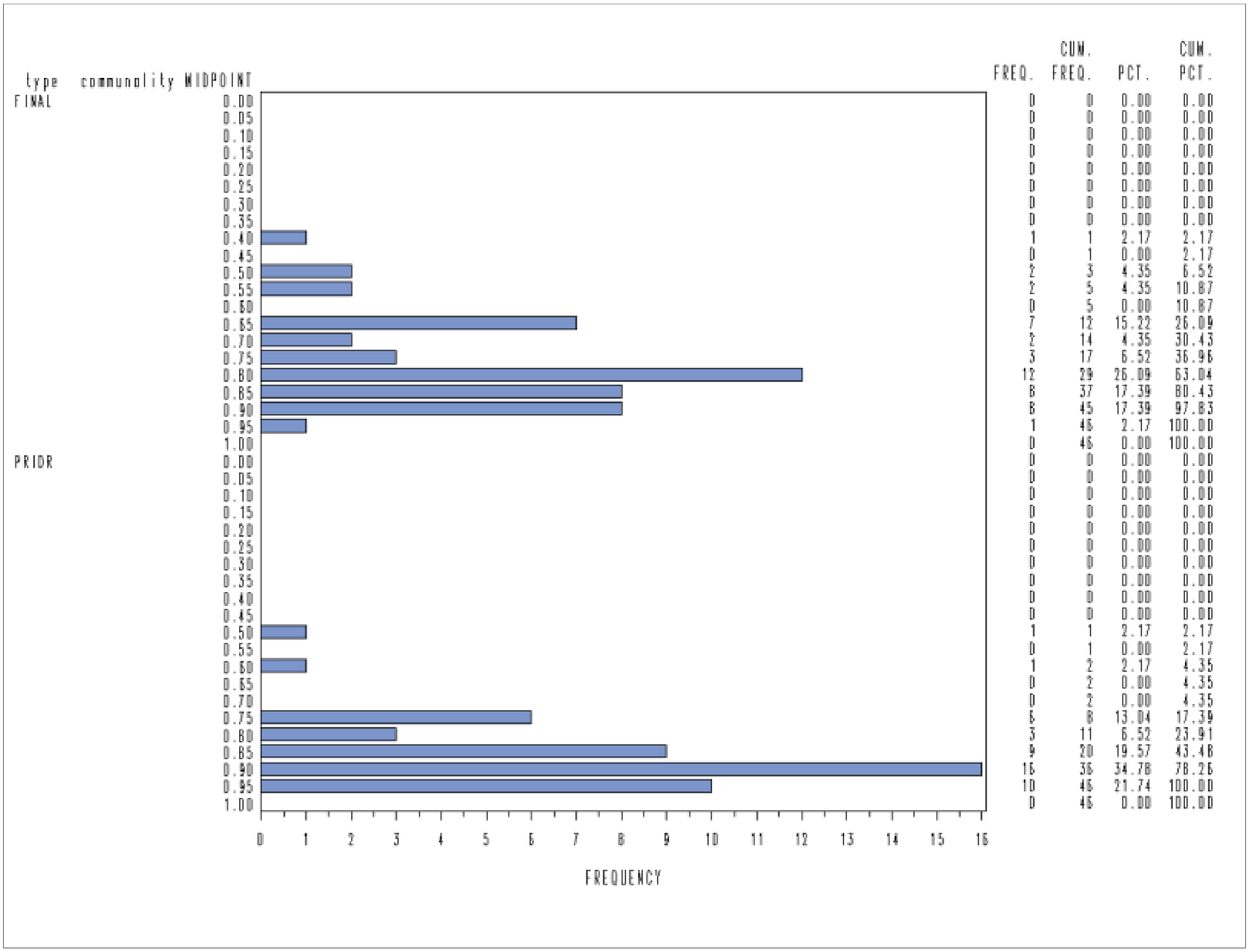


Figure 13. Scree plot of eigenvalues for the combined item pool from all four surveys at the OU-mean unit of analysis.

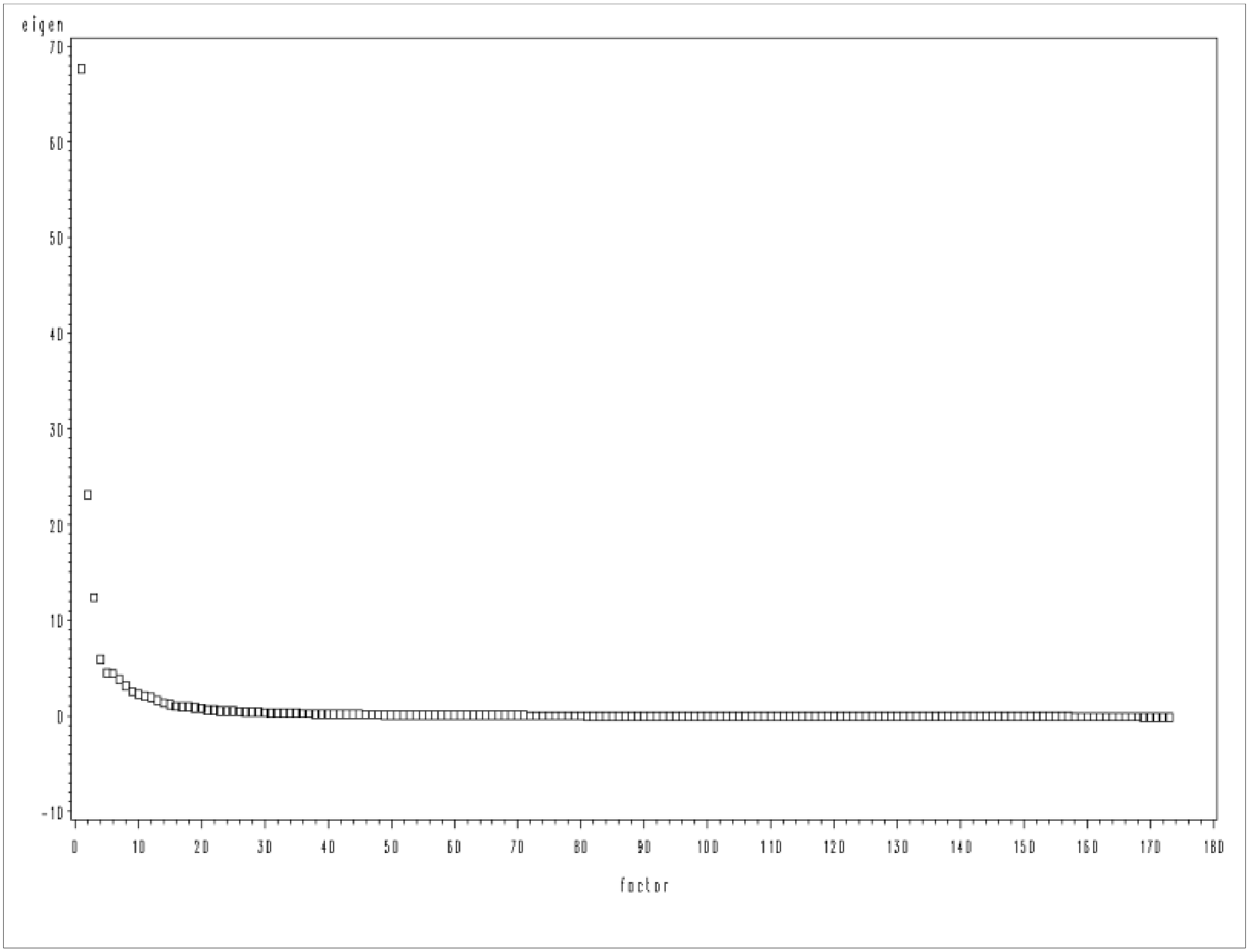


Figure 14. Final communality values for the 4-factor solution (top) and prior (SMC) communality estimates for the combined four-survey item pool at the OU-mean unit of analysis.

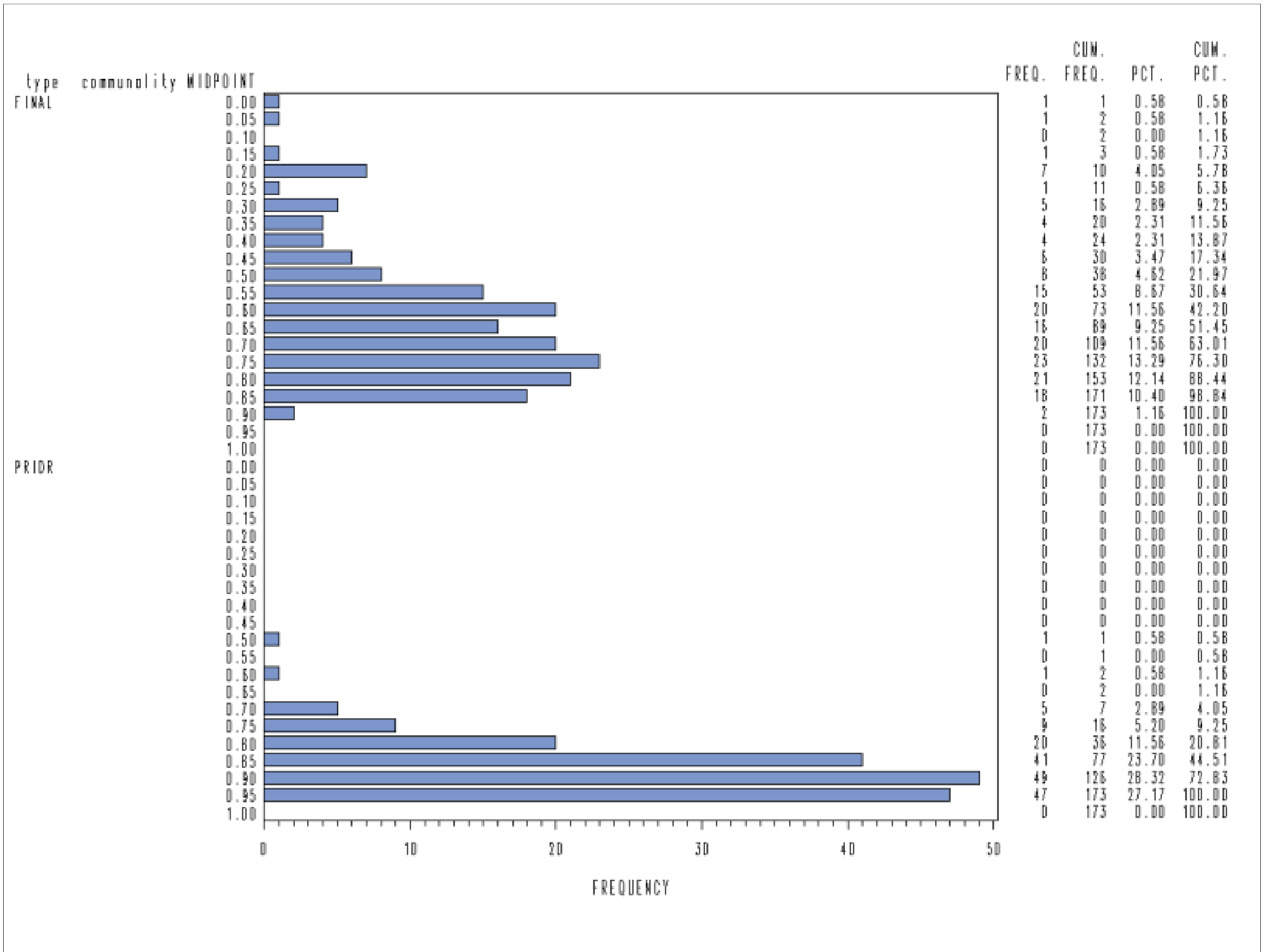


Figure 15. Scree plot for combined *GWAs* and *Skills* item pools at the OU-mean unit of analysis.

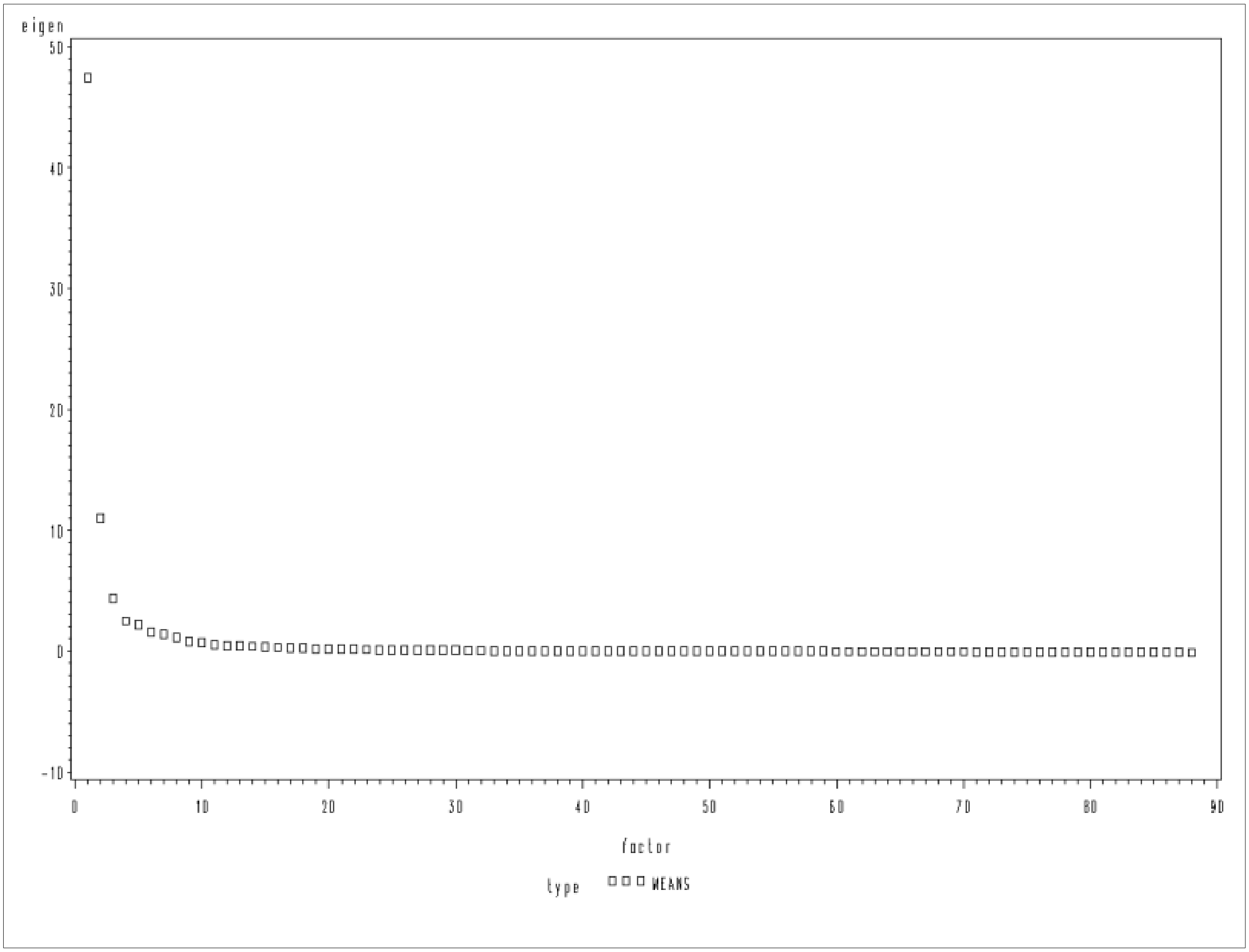
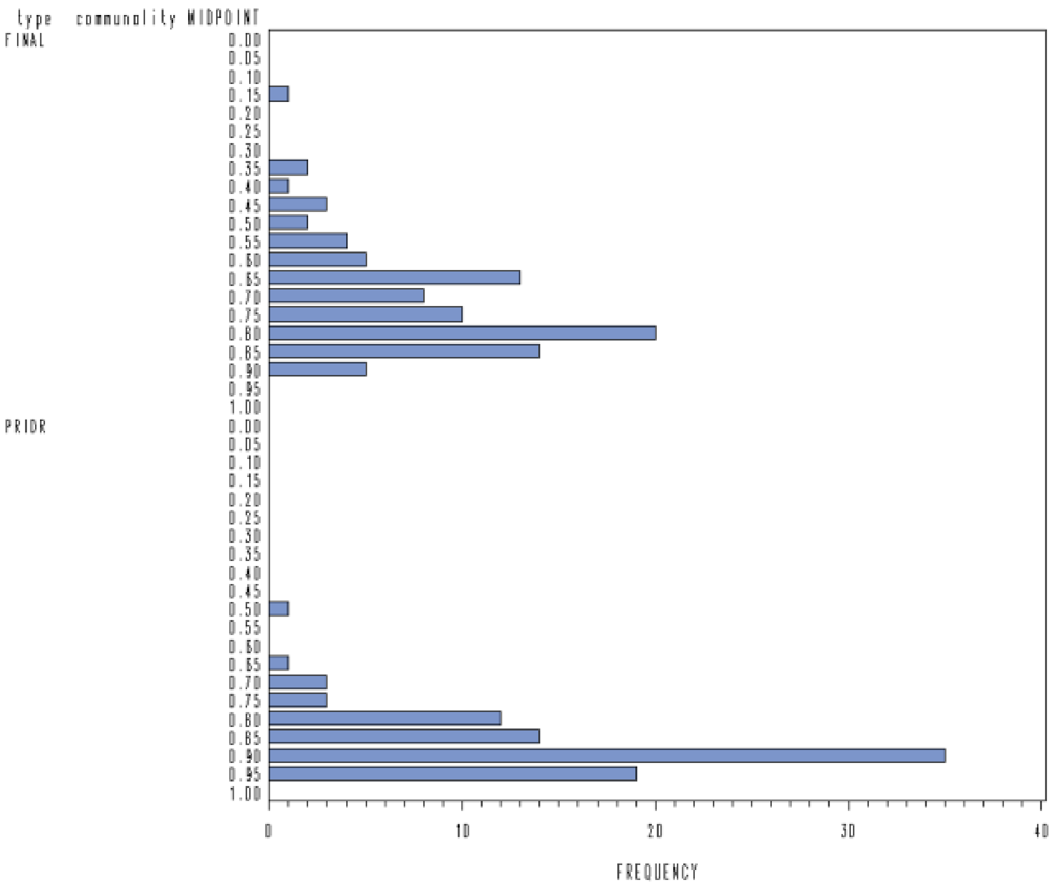


Figure 16. Final communality values for the 3-factor solution (top) and prior (SMC) communality estimates for the combined *GWAs* and *Skills* item pools at the OU-mean unit of analysis.



type	communality MIDPOINT	FREQ.	CUM. FREQ.	PCT.	CUM. PCT.
FINAL	0.00	0	0	0.00	0.00
	0.05	0	0	0.00	0.00
	0.10	0	0	0.00	0.00
	0.15	1	1	1.14	1.14
	0.20	0	1	0.00	1.14
	0.25	0	1	0.00	1.14
	0.30	0	1	0.00	1.14
	0.35	2	3	2.27	3.41
	0.40	1	4	1.14	4.55
	0.45	3	7	3.41	7.95
	0.50	2	9	2.27	10.23
	0.55	4	13	4.55	14.77
	0.60	5	18	5.68	20.45
	0.65	13	31	14.77	35.23
	0.70	8	39	9.09	44.32
	0.75	10	49	11.36	55.68
	0.80	20	69	22.73	78.41
	0.85	14	83	15.91	94.32
	0.90	5	88	5.68	100.00
	0.95	0	88	0.00	100.00
	1.00	0	88	0.00	100.00
PRIOR	0.00	0	0	0.00	0.00
	0.05	0	0	0.00	0.00
	0.10	0	0	0.00	0.00
	0.15	0	0	0.00	0.00
	0.20	0	0	0.00	0.00
	0.25	0	0	0.00	0.00
	0.30	0	0	0.00	0.00
	0.35	0	0	0.00	0.00
	0.40	0	0	0.00	0.00
	0.45	0	0	0.00	0.00
	0.50	1	1	1.14	1.14
	0.55	0	1	0.00	1.14
	0.60	0	1	0.00	1.14
	0.65	1	2	1.14	2.27
	0.70	3	5	3.41	5.68
	0.75	3	8	3.41	9.09
	0.80	12	20	13.64	22.73
	0.85	14	34	15.91	38.64
	0.90	35	69	39.77	78.41
	0.95	19	88	21.59	100.00
	1.00	0	88	0.00	100.00