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Are there distinct cognitive types?

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ABSTRACT

A few previous attempts to isolate cognitive types—groups of individuals with similar profiles of cognitive skills—have been reported in the literature. For the most part, they have not arrived at the same types. The present study sought to identify cognitive types via cluster analysis in an available sample of adolescent twins. Analyses were carried out using one randomly selected twin from each of 16-year-old Australian twin pairs who had taken a five-scale cognitive test battery ($N = 677$ pairs—a further sample of 628 pairs was reserved for replication purposes). Three levels of tightness of clusters were examined—minimum mutual intercorrelations among cluster members of 0.10, 0.30 and 0.50. The higher intercorrelations led to more clusters—18 at the 0.10 criterion, 25 at 0.30, and 36 at 0.50. The 0.10 level was most similar to the number of clusters reported in previous studies, and was chosen for further analysis. Clustering at this level yielded 18 clusters of individuals from the random twins, and 17 from their co-twins. Fifteen of these matched, as evidenced by a correlation of 0.80 or more between the cluster means. A second method of clustering based on a different approach, SPSS Cluster, gave similar results—15 clusters matched those from the original analysis. Agreement for cluster membership was compared for identical and fraternal twins. A greater agreement for identical twin pairs was found, and interpreted as evidence of a genetic contribution to the clustering. Most of the above analyses were successfully replicated on the reserved sample of twin pairs. Thus there was evidence for stability of initial clustering in this population. However there was not much evidence across studies for discrete and dependable cognitive types.

1. Introduction

Typologies, i.e., groups of people with similar characteristics, provide one way of looking at the differences among individuals. For personality or temperament types, there is a long history dating back at least to the second century AD with Galen's Sanguine, Choleric, Melancholic, and Phlegmatic temperaments, based on Hippocrates' theory of four humors. The possibility that humans could be divided into categories based on their patterning of cognitive skills has been less thoroughly explored. There has been some interest arising out of the Jungian tradition (e.g., Jung, 1921/1976), which emphasizes direction (introversion, extraversion) and mode (sensation, feeling, thinking, and intuition) rather than the patterning of cognitive skill as such. By contrast, there have been a great many analyses of *dimensions* of cognitive skill, dating from the factor analyses of Spearman (1904); see, e.g., Brody (1992) or Carroll (1993). Describing cognitive types is different from, although related to, describing dimensions of cognitive skill. A cluster analysis, an empirical way of approaching cognitive types, is complementary to, not in conflict with, a dimensional analysis, such as a factor analysis of tests. A factor analysis of tests defines a space. A cluster analysis of persons then asks if individuals group in clusters within that space.

Why might one be interested in the existence of cognitive skill clusters? Such clustering might provide clues to the evolutionary history of cognition, or to current brain organization. There may be practical implications as well. From the standpoint of education, if there proved to be a fairly small number of well-defined cognitive types, one could consider putting their members into different educational streams, in order to provide them with educational experiences appropriate to their different skill sets.

There have been some speculative cognitive typologies (e.g., Maruyama, 2003), but until recently there have been relatively few empirical studies attempting to define the clustering of persons on cognitive skills, and most of these studies have involved samples of individuals with intellectual or emotional disabilities (e.g., Hale, Casey, & Ricciardi, 2014; Poletti, Carretta, Bonvicini, & Giorgi-Rossi, 2018; Uren, Cotton, Killackey, Saling, & Allott, 2017).

However, cognitive clustering among normal individuals has not been entirely neglected. A pioneering empirical study was that of Tryon (1967), who distinguished 15 cognitive types among the 301 Chicago schoolchildren given 24 cognitive tests by Holzinger and Swineford (1939). Tryon used his own clustering program. The 15 cognitive types he obtained could be described by performance on four cognitive dimensions (Verbal, Speed, Form, and Memory). For example, one cluster consisted of individuals who had a relatively high score on just the Verbal dimension—22 children belonged to this cluster. Additional

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clusters were formed by individuals with a relatively high score on one of the other three dimensions. Another four clusters were defined by those with a low score on one of the dimensions. Four more clusters featured low scores on a pair of dimensions, e.g., Verbal and Memory. Two were defined by high scores on a pair. One cluster had scores in the average range on all four dimensions. No cluster was defined by a combination of a high score on one dimension and a low score on another. The largest cluster, no high or low extremes, consisted of 44 children. Others ranged from 8 to 26.

In a study also relevant to the present investigation, nine subgroups of persons were located by cluster analysis in a normal set of individuals—1880 members of the WAIS-R standardization sample (McDermott, Glutting, Jones, & Noonan, 1989). However, 6 of the 9 types were defined primarily by overall level of performance rather than by distinctive cognitive trait profiles (Schinka & Vanderploeg, 1997). Schinka and Vanderploeg did a cluster analysis based on a set of 341 individuals from the same sample who exhibited relatively marked variation across the WAIS-R subtests. They again found 9 clusters of individuals, but they were not the same ones. Only one was characterized, as were the McDermott et al. clusters, by a relatively uniform level of performance across subtests (a high level). A second cluster showed higher performance on the Verbal than on the Performance subscales, and a third was characterized by a low performance on the Performance scales. Three of the remaining six clusters were defined by a high score on a single subtest, two by a high and low pair, and one by a high and several lows. Unlike Tryon's, no cluster was defined by a single low subtest score, and also unlike Tryon's, there were a number of clusters defined by both high and low scores.

One purpose of the present investigation was to see whether clusters derived in a different way on a different sample of individuals arrived at cognitive clusters or “cognitive types” resembling those found in preceding studies. A second purpose, because the sample consisted of identical (MZ) and fraternal (DZ) twins, was to assess the role of the genes in defining the clusters. If a pair of MZ twins is more likely to belong to the same cognitive cluster than a pair of DZ twins, genetic involvement in the clustering is suggested.

The sample used consisted of Australian twins. These were adolescent twins who had been administered tests from the Multidimensional Aptitude Battery (MAB) at approximately age 16. The clustering was based on the five subtests used: Information, Arithmetic, Vocabulary, Spatial Ability, and Object Assembly. The questions addressed include: Does distinctive clustering of individuals based on cognitive skills occur? Do the clusters resemble those found by previous investigators? To what extent is the clustering genetically influenced? And from a more methodological perspective: how does the clustering compare across two clustering methods and three different levels of tightness of clustering?

2. Method

2.1. The sample

The total sample consisted of 521 MZ and 784 DZ Australian twin pairs in which both members were tested. The twins were chiefly recruited through schools in the Brisbane area as part of the ongoing Brisbane Memory, Attention, and Problem-Solving Study (Wright & Martin, 2004), and were tested close to their 16th birthdays. As is typical of volunteer samples, females moderately exceeded males, 288 to 253 among MZs and 417 to 367 among DZs. The twins were administered an ability test battery along with other measures in a 1½ hour testing session, preceded or followed by a similar session measuring event-related potentials. The order of session testing was counterbalanced according to the birth order of the twins—for details see Wright et al. (2001). For our purposes, the total sample was randomly divided into two subsamples, one for the original analyses ($N = 667$ pairs) and one for replication ($N = 628$ pairs). The sexes were combined for the analyses in order to obtain adequate sample sizes—earlier work with the present sample had indicated that the same genetic model could be fit in both sexes, and that the phenotypic correlations among the subtests did not differ significantly by sex (Luciano et al., 2003).

2.2. The measures

The ability test taken by the twins was a shortened version of the Multidimensional Aptitude Battery (MAB, Jackson, 1998). The battery was administered by computer, except for the performance tests early in the study. Five MAB subtests were used, all in multiple-choice format and timed at 7 min each: Information (40 items), which examines general knowledge of persons, places, and events; Arithmetic (25 items), which consists of verbally-stated mathematics problems e.g. “How much do three books cost, if they are four dollars each?”; Vocabulary, which measures knowledge of word meanings, where participants identify the synonym from a list of five words (46 items); Spatial Ability (50 items), which assesses spatial rotation of various shaped figures, where a match is selected from one of five possible rotations, including ‘flipped-over’ permutations as distractors; Object Assembly (20 items), which requires reassembling disjointed pieces of an object to form its regular shape. The test-retest reliabilities of the subtests in a subset of the present sample were estimated as 0.83, 0.67, 0.77 0.77, and 0.67, respectively (Luciano et al., 2003).

2.3. The analyses

As noted, the 1305 twin pairs were randomly divided into two subgroups of 677 and 628 pairs, the first for the basic analyses, the second reserved for replication. One individual from each twin pair in the basic sample was randomly selected, and these 677 individuals intercorrelated across the 5 MAB subtests, yielding a 677 × 677 matrix of resemblances among them that served as the basis for forming clusters of similar individuals. One algorithm for the clustering of individuals was that used by Loehlin and Martin (2018), adapted from a procedure used for the clustering of test items by Loehlin and Nichols (1976). We will refer to this as the “Successive Cluster” method. The other clustering procedure was a version of the SPSS program Cluster, which forms clusters considering all individuals and clusters at each step.

The first, the Successive Cluster method, proceeded as follows: The analysis began with a 677 × 677 correlation matrix among individuals (one from each twin pair). The first cluster was started with the two most highly correlated individuals. The person having the highest minimum correlation with the current members of the cluster was then added to it, and this process repeated until the lowest correlation of a new member with the existing members of the cluster dropped below a threshold—for the initial analysis set at 0.30. That is, each member of a cluster correlated at least 0.30 with every other member. The cluster was then removed from the matrix, and the highest correlation among the remaining members taken as the start of a new cluster. This process was repeated until no new cluster could be formed—that is, until the highest correlation among the remaining individuals was less than 0.30. Mean scores on the five subscales were calculated for each of the obtained clusters, to provide a descriptive profile.

Next the SPSS Cluster program was used on the same data set. Its parameters were set to correspond roughly to the first program—correlation was used for the distance measure, and average linkage within groups was minimized. However, the program proceeded in a quite different sequence, beginning with every individual considered as a group, and at each step merging the two groups that resulted in the least increase in the criterion. For comparison purposes, results were viewed at the same number-of-clusters levels as those obtained with the Successive Clusters program.

The effects of using lower and higher clustering criteria in the

Successive Clusters program (correlations of 0.10 and 0.50, instead of 0.30) were examined. In each case results from the SPSS Cluster program were compared for the same number of clusters. Means over the five subtests were calculated to describe the SPSS clusters, and were compared to the cluster means from the Successive Clusters program—a correlation of 0.80 or higher was taken as evidence that essentially the same cluster had been obtained by the two methods. (If such correlations with more than one cluster in the other set were obtained, as happened in a few cases, the higher was used.) For the clusters matching across sets, the mean of their (similar) means for the two programs was taken as a final description of the cluster.

Next, the twins not used in the clustering were themselves clustered in the same manner, and the two sets matched.

Finally, agreement on cluster membership was obtained for each pair of twins. Agreement higher for MZ than for DZ pairs was taken as evidence of a genetic contribution to the clustering. In addition, the correlations between the profiles for MZ and DZ pairs were compared with correlations for the traits themselves.

For the replication, the clustering was carried out in the same way in the reserved sample, and the resulting clusters compared with those in the original analysis. Again, matching was compared for MZ and DZ twins to assess genetic and environmental effects on the clustering.

Note that both clustering methods were based on correlations among trait profiles, so that the resulting clusters were derived from patterns of cognitive strengths and weaknesses rather than overall levels of performance. Schinka and Vanderploeg (1997) also used correlation as a similarity measure in their cluster analyses. Overall level of performance had dominated in the McDermott et al. (1989) clustering, which used a distance measure of resemblance between persons.

3. Results and discussion

3.1. Basic clustering

Table 1 shows the general properties of the clustering at three levels of cluster tightness for the two programs.

The number of clusters is the same for the two programs, because the SPSS program results are reported for the level that corresponded to the number obtained by the Successive Cluster program. More clusters were obtained with higher criteria for clustering, in both the original and replication samples. There was a tendency for this to result in smaller maximum-sized clusters as well, particularly at the 0.50 level.

That clusters would be larger when a looser criterion is used is not surprising, especially with the Successive Cluster method—as the criterion is lowered, more cases can get added to clusters before they are closed off. The other fact—that more clusters were found with a stricter criterion—is not so obvious. In principle, a stricter criterion might lead to fewer clusters and more unclustered individuals.

Because the number of clusters obtained with the 0.10 criterion was closer to that in the three studies discussed earlier—15 in Tryon's and 9 in Schinka's and in McDermott's—further analyses and discussion will be focused on this level.

Table 1
General properties of the cognitive clustering at three levels for two programs in original and replication samples.

Program	Crit. 0.10		Crit. 0.30		Crit. 0.50	
	NC	LC	NC	LC	NC	LC
Analysis sample (N = 677)						
Successive Cluster	18	67	25	67	31	65
SPSS	18	83	25	56	31	48
Replication sample (N = 624)						
Successive Cluster	18	67	22	67	33	50
SPSS	18	70	22	68	33	57

Note: Crit. = clustering criterion; NC = number of clusters; LC = largest cluster.

3.2. Are the obtained clusters dependable?

In the majority of cases, each cluster found by one clustering method matched a cluster found by the other clustering method, as evidenced by a correlation of 0.80-plus between their profiles. At the 0.10 criterion level, the pattern of means of 14 of the 18 clusters obtained in the original clustering correlated at least 0.80 with that of a cluster obtained at the 18-cluster level in the SPSS clustering. This, despite the fact that their strategies were quite different. The first method worked successively, finding and removing clusters one at a time. The SPSS method worked concurrently, at each step merging two clusters or adding a person to an existing cluster. That they would agree quite well at a given number-of-clusters level is evidence of true clustering in the data sample in question. The issue then becomes: are the same clusters found in other data samples?

As a first step, we asked: If we carry out the clustering on the twins of the initial sample, do we find the same clusters? The answer was, yes, mostly. Fifteen of the 18 clusters found with one random twin from each pair were found when clustering their twins, by the criterion of a correlation of 0.80 or better between the mean profiles of the clusters. What were these clusters like? Table 2 shows the averaged profiles for the 15 matching clusters. The original scores are on standard-score scales, so that a score of 0.00 on a subtest represents an average score on this subtest, a score of −0.50 indicates half a standard deviation below the mean for this group, and a score of +0.50 half a standard deviation above. Means beyond ± 0.50 are shown in boldface type in the table. For convenience of discussion, the profiles are arranged in the table by profile type: single peak or valley, pair of peaks/valleys, etc.

The profiles of the first three clusters in the table are marked by a single valley or peak, defined as one that is more than half a standard deviation from the overall mean, and at least twice that of the next most extreme. The first two of these profiles are peaks—high scores on Arithmetic and Information. The third is a valley—what the cluster members share is poor performance on Arithmetic.

The next 9 clusters in the table are defined by a pair of points beyond ± 0.50. All but one of them involve one peak and one valley. That is, what the cluster members share is one strength and one weakness. In the exception, cluster 8, it is two weaknesses, on Object Assembly and Information (with a third, Spatial Ability, close); this does not represent simple incompetence, as Vocabulary is modestly above the mean. The remaining paired peaks and valleys involve all the subtests, but if one

Table 2
Profiles of clusters at the 0.10 criterion level matching between Twin A and Twin B samples.

	Inf	Ari	Voc	Spa	Obj
1.	−0.10	**1.11**	−0.12	0.08	−0.26
2.	**1.00**	−0.17	−0.23	−0.40	−0.17
3.	0.17	**−0.94**	−0.03	0.43	0.27
4.	0.38	−0.41	**0.86**	**−0.86**	−0.06
5.	0.12	**0.73**	−0.08	**−0.98**	−0.15
6.	−0.09	−0.34	**−0.84**	**0.75**	−0.14
7.	**−0.89**	0.06	−0.41	**0.64**	−0.16
8.	**−0.62**	0.01	0.32	−0.49	**−0.88**
9.	**−0.90**	**0.58**	−0.30	−0.16	0.35
10.	0.18	**0.54**	−0.34	0.33	**−0.82**
11.	**0.55**	**−0.75**	0.06	0.08	0.18
12.	0.47	0.40	**−0.64**	0.25	**0.65**
13.	**0.67**	−0.06	**0.54**	−0.32	**−0.94**
14.	**−0.66**	−0.25	**−0.62**	**0.55**	**0.78**
15.	**−0.51**	−0.30	0.03	0.23	0.47

Note: Inf = Information; Ari = Arithmetic; Voc = Vocabulary; Spa = Spatial Ability; Obj = Object Assembly. Values are means of Twin A and Twin B clusters that match. Means beyond ± 0.50 in boldface.

Table 3
The Table 2 analysis in the replication sample.

	Inf	Ari	Voc	Spa	Obj	T2
1.	**1.11**	0.31	0.18	−0.30	0.21	2
2.	0.23	0.25	0.29	**−1.07**	−0.17	5
3.	0.03	**0.96**	−0.07	−0.22	−0.39	1
4.	**0.94**	0.19	−0.21	−0.15	0.29	2
5.	**−0.94**	**−0.91**	0.09	0.02	0.10	15
6.	0.03	−0.18	**0.94**	−0.30	**−0.84**	13
7.	0.49	−0.27	**1.01**	0.23	**0.73**	
8.	**0.57**	−0.21	**1.03**	−0.35	−0.45	4
9.	0.40	**0.52**	−0.16	−0.23	**−0.79**	10
10.	0.40	**−0.70**	−0.41	**0.53**	0.09	3
11.	−0.10	**−0.63**	**−0.65**	−0.10	**0.75**	
12.	0.00	**0.79**	**−0.64**	**0.52**	−0.03	
13.	−0.15	**0.55**	−0.40	**−0.51**	**0.59**	
14.	**−0.64**	0.07	**−0.81**	**0.63**	**0.59**	14

Note: Inf = Information; Ari = Arithmetic; Voc = Vocabulary; Spa = Spatial Ability; Obj = Object Assembly. Values are means of matching Twin A and Twin B clusters. Means beyond ± 0.50 in boldface. T2 = Table 2 equivalent cluster.

defines the first three (Information, Arithmetic, and Vocabulary) as Verbal subtests, and the last two (Spatial Ability and Object Assembly) as Performance subtests, the peak tends to come in one group and the valley in the other.

The 13th and 14th clusters involve three or four peaks or valleys: two peaks and a valley for the former, and two of each for the latter. The 15th is somewhat nondescript—it has one test barely beyond ± 0.50, and one barely below. On the whole, it most resembles the paired peaks.

Do these clusters replicate? To some degree. Table 3 shows the same analysis based on the 628-pair replication sample. The clusters are arranged in the table in parallel fashion to Table 2—clusters defined by a single test in the first rows of the table, two-test clusters next, etc. The extreme right-hand column indicates correspondences with Table 2 clusters.

The Table 3 analysis obtained almost the same number of clusters as the Table 2 analysis—14 versus 15. The first four rows of Table 3 show single-test clusters; there were three in Table 2. Table 3 had fewer two-test clusters—six versus the nine in Table 2. Half of those in Table 3 were marked by two peaks or two valleys, as opposed to only one of nine in Table 2. Table 3 had three clusters marked by three tests, Table 2 had one. Each table had one four-test cluster, and they were of the same configuration—highs on Spatial Ability and Object Assembly, and lows on Comprehension and Vocabulary, with Arithmetic in between, suggesting a Verbal/Performance contrast.

The majority of the Table 3 clusters—10 of the 14—had profiles that correlated at a level of 0.80 or higher with a cluster in Table 2. Table 4 shows the results of averaging these two sets of profiles.

Four were single peak or valley profiles—three peaks, one valley. Four were pairs—one with two peaks, one with two valleys, two with one of each. Cluster 9 was a foursome—two peaks, two valleys. Cluster 10 is bit anomalous—it doesn't quite satisfy the one-peak definition—the peak is not double the next highest score—and the second peak is a few points short of qualifying it as a two-peak cluster.

Table 4
Profiles of replicated clusters.

@	Inf	Ari	Voc	Spa	Obj
1.	**1.06**	0.07	−0.02	−0.35	0.02
2.	0.18	0.49	0.10	**−1.02**	−0.16
3.	−0.04	**1.02**	−0.10	−0.07	−0.32
4.	**0.97**	0.01	−0.22	−0.28	0.06
5.	**−0.72**	**−0.60**	0.06	0.12	0.28
6.	−0.30	−0.08	**0.63**	−0.40	**−0.86**
7.	0.48	−0.31	**0.94**	**−0.66**	−0.26
8.	0.29	**0.53**	−0.25	0.05	**0.80**
9.	**−0.63**	−0.09	**−0.71**	**0.59**	**0.68**
10.	0.28	**0.82**	−0.22	0.48	0.23

3.3. Comparison with earlier studies

How do these configurations resemble those obtained by previous authors? Excluding the McDermott et al. (1989) study, which featured overall levels, there are roughly comparable numbers of clusters defined by single peaks or valleys. Table 4 shows 4 out of 10 for the present study—three with peaks, one with a valley. Of Tryon's 15 clusters (Tryon, 1967), 8 had single peaks or valleys, 4 of each. Of Schinka and Vanderploeg's 9 clusters (Schinka & Vanderploeg, 1997), 3 were marked by single peaks.

Three of the remaining cluster profiles in Table 4 involve both high and low scores. This is different from Tryon, who had no clusters marked by both peaks and valleys, but is comparable to Schinka and Vanderploeg—3 of 9 in their Table 2 (Schinka & Vanderploeg, 1997).

Comparing content is more difficult, since the three studies' profiles were based on different tests. Tryon found clusters of persons high on Verbal, Speed, Form, or Memory dimensions, and clusters of persons low on each. Our single-peak clusters were Information (two) and Arithmetic, and our single-valley cluster Spatial Ability. Schinka and Vanderploeg's single peaks were on Performance rather than Verbal tests—Picture Completion, Picture Arrangement, and Digit Symbol. As noted, Tryon had no clusters marked by both peaks and valleys. Three of Schinka and Vanderploeg's clusters marked by both peaks and valleys provided a Verbal/Performance contrast—the remaining one involved two Verbal subscales. Thus there were some resemblances in general form across the studies, but few one-to-one matches of "cognitive types."

The results for cognitive clustering were also generally similar in form to those obtained by Loehlin and Martin (2018) for personality types, based on a large sample of adult Australian twins. The general pattern of more numerous clusters as the criterion for cluster membership moved from 0.10 to 0.30 to 0.50 held for both, and a variety of patterns—single peaks or valleys, or pairs or other more complex patterns of high or low scores characterized the obtained clusters.

3.4. MZ versus DZ matching

Are MZ pairs more often in the same clusters than DZ twins are? Yes. In the original sample the two MZ twins were in matched clusters (as in Table 2) 16.0% of the time, whereas for DZ twins it happened 12.3% of the time. In the replication sample, the corresponding figures were 13.5% and 7.4%. A greater similarity for MZ pairs suggests genetic effects—MZ twins share all their genes, but DZ twins share only half. (A bit more than half, if parents are correlated for the trait in question. Such parental correlations are substantial for general intelligence, but more modest for specific cognitive traits. We know of no evidence concerning trait profiles. At any rate, parental genetic resemblance would tend to decrease apparent genetic effects, as it would raise the resemblance for DZ pairs while not affecting that of MZ pairs.)

Table 5 looks at this from a somewhat different perspective. It shows

Table 5
Correlations for MZ and DZ pairs for traits and profiles, 0.10 criterion.

Category	MZ pairs	DZ pairs
Analysis sample (N = 677)		
Average for traits	0.63	0.34
Average for profiles	0.40	0.17
Replication sample (N = 628)		
Average for traits	0.63	0.29
Average for profiles	0.36	0.14

the extent to which members of twin pairs were similar for individual traits or trait profiles, depending on whether they were identical (MZ) or fraternal (DZ). Again, the greater similarity of the MZ twins suggests genetic effects.

The correlations are higher for the traits than for the profiles—-which might just reflect a greater reliability of measuring the former. However for both traits and profiles in both samples the correlation for MZ pairs is greater than that for the DZ pairs, suggesting a genetic contribution. In the case of the traits, the MZ correlation is close to twice the DZ correlation, suggesting a largely additive genetic contribution—i.e., the adding together of the effects of individual genes. For the profiles, the MZ correlation exceeds twice the DZ correlation, suggesting at least some nonadditive genetic contribution—i.e., the effects of some genes depending on the presence of others. Such interdependence seems appropriate for clusters.

3.5. Limitations

This is a sample of late-adolescent twins from Australia, and further research will be required to see if the results generalize to other ages and tests, or various additional methods of clustering, or differ for the two sexes or in different cultures.

4. Conclusion

As in the case of earlier studies, there was evidence of clustering of individuals on cognitive skills within a given sample. However, there was less evidence for "cognitive types" consistent across studies. Clustering based on a single shared cognitive skill or deficiency was present, as was clustering based on the configuration of two or more skills and deficiencies. Sometimes, but not always, the latter involved Verbal/Performance contrasts. Comparison of MZ and DZ twin pairs suggested that the genes were to some degree involved in the clustering, perhaps in a non-additive fashion.

Thus, on the whole there was evidence for stability at the level of initial clustering, both across methods and subsamples, but little evidence of discrete and dependable cognitive types.

References

Brody, N. (1992). *Intelligence* (2nd ed.). New York: Academic Press.

Carroll, J. B. (1993). *Human cognitive abilities: A survey of factor-analytic studies.* Cambridge: Cambridge University Press.

Hale, C. R., Casey, J. E., & Ricciardi, P. W. R. (2014). A cluster analytic study of the Wechsler Intelligence Test for Children-IV in children referred for psychoeducational assessment due to persistent academic difficulties. *Archives of Clinical Neuropsychology, 29*, 75–85.

Holzinger, K. J., & Swineford, F. (1939). A study in factor analysis. *Supplementary educational monographs*. *Vol. 48*. Chicago: University of Chicago Department of Education.

Jackson, D. N. (1998). *Multidimensional aptitude battery II.* Port Huron,MI: Sigma Assessement Systems.

Jung, C. G. (1921/1976). *Psychological types.* London: Routledge.

Loehlin, J. C., & Martin, N. G. (2018). Personality types: A twin study. *Personality and Individual Differences, 122*, 99–103.

Loehlin, J. C., & Nichols, R. C. (1976). *Heredity, environment, and personality.* Austin, TX: University of Texas Press.

Luciano, M., Wright, M. J., Geffen, G. M., Geffen, L. B., Smith, G. A., Evans, D. M., & Martin, N. G. (2003). A genetic two-factor model of the covariation among a subset of multidimensional aptitude battery and Wechsler adult intelligence scale—Revised subtests. *Intelligence, 31*, 598–605.

Maruyama, M. (2003). Individual cognitive/cogitative types. *International Review of Sociology, 13*, 545–565.

McDermott, P. A., Glutting, J. J., Jones, J. N., & Noonan, J. V. (1989). Typology and prevailing composition of core profiles in the WAIS-R standardization sample. *Psychological Assessment, 1*, 118–125.

Poletti, M., Carretta, M. S., Bonvicini, L., & Giorgi-Rossi, P. (2018). Cognitive clusters in specific learning disorders. *Journal of Learning Disabilities, 51*, 32–42.

Schinka, J. A., & Vanderploeg, R. D. (1997). Profile clusters in the WAIS-R standardization sample. *Journal of the International Neuropsychological Society, 3*, 120–127.

Spearman, C. (1904). "General intelligence" objectively determined and measured. *American Journal of Psychology, 15*, 201–293.

Tryon, R. C. (1967). Person-clusters on intellectual abilities and on MMPI attributes. *Multivariate Behavioral Research, 2*, 5–34.

Uren, J., Cotton, S. M., Killackey, E., Saling, M. M., & Allott, K. (2017). Cognitive clusters in first-episode psychosis: Overlap with healthy controls and relationship to concurrent and prospective symptoms and functioning. *Neuropsychology, 31*, 787–797.

Wright, M. J., De Geus, E., Ando, J., Luciano, M., Posthuma, D., Ono, Y., ... Boomsma, D. (2001). Genetics of cognition: Outline of a collaborative twin study. *Twin Research, 4*, 48–56.

Wright, M. J., & Martin, N. G. (2004). Brisbane adolescent twin study: Outline of study methods and research projects. *Australian Journal of Psychology, 56*, 65–78.