

## **Creativity and Intelligence Revisited: A Latent Variable Analysis of Wallach and Kogan (1965)**

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### **Abstract:**

Many decades of research have shown that creativity and intelligence are modestly related. Some studies, however, have found that creativity and intelligence are essentially unrelated. The best example may be Wallach and Kogan's (1965) landmark study of 151 children. In that study, 10 measures of creativity didn't correlate with 10 measures of intelligence and academic achievement (average  $r = .09$ ). The present research reanalyzed these data using latent variable analysis, which can (a) assess the relations between latent creativity and intelligence variables and (b) model method variance shared by the creativity tasks. Consistent with past research, the latent originality and fluency variables significantly predicted intelligence. The relations' magnitude (around  $r = .20$ ) was consistent with past research, suggesting that Wallach and Kogan's data replicate other studies of creativity and intelligence.

### **Article:**

The study of creativity and intelligence is one of the oldest areas of creativity research, perhaps because of Guilford's (1950, 1967) landmark work in both fields. Psychometric research generally finds modest relationships between creativity and intelligence—within the range of  $r = .10$  to  $.30$ —depending upon the nature of the creativity and intelligence tests and the range of intelligence in the sample (Kim, 2005; Sternberg & O'Hara, 1999). Creativity tests that involve convergent thinking, such as the Remote Associates Test, typically show higher correlations with intelligence (e.g., Kane et al., 2004; Mednick & Andrews, 1967) relative to creativity tests that involve divergent thinking, such as alternate uses tests (e.g., Plucker, 1999; Preckel, Holling, & Wiese, 2006). In an analysis of nearly 400 correlations, Torrance (1975) concluded that creativity and intelligence are only modestly related. Consistent with Torrance's conclusion, a recent meta-analysis found an overall creativity-intelligence relation of  $r = .174$  (Kim, 2005).

In light of the consistently modest relations between creativity and intelligence, studies that found essentially no relationship are particularly interesting. Perhaps the best-known study is Wallach and Kogan's (1965) classic research on creativity and intelligence in fifth-grade children. Wallach and Kogan administered 5 measures of creativity, each of which yielded a score for originality and fluency, and 10 measures of intelligence and achievement to 70 boys and 81 girls. The creativity tests were given in a casual, game-like atmosphere, which was expected to facilitate creativity. Wallach and Kogan found that the creativity tests correlated strongly with each other (average  $r = .41$ ), that the intelligence and achievement tests correlated highly with each other (average  $r = .51$ ), but that the creativity tests did not correlate with the intelligence tests (average  $r = .09$ ).

This pattern—unrelated sets of coherent creativity and intelligence tests—set Wallach and Kogan's (1965) research apart from similar studies. Getzels and Jackson's (1962) classic study, for instance, was unable to achieve strong internal consistency between the tests. The creativity tests correlated as highly with the intelligence tests as they did with each other, which implies a single latent factor. Moreover, critics of their study (McNemar, 1964) estimated the relation between creativity and intelligence to be  $r = .40$ , higher than Getzels and Jackson thought. Wallach and Kogan's study thus represents an unusually good example of an instance in which creativity and intelligence were essentially unrelated.

Wallach and Kogan's (1965) study, although undoubtably sophisticated for its time, was limited by the state of statistical knowledge (cf. Cronbach, 1968). In 1965, researchers were unable to do much with multiple measures of a single construct. In modern research, Wallach and Kogan's data would be modeled with latent variable analysis, which uses observed variables to estimate relationships between latent constructs (Kline, 2005; Loehlin, 2004). Apart from its many statistical benefits—the ability to model method variance among them—latent variable analysis fits the view of creativity and intelligence as abstract *latent factors* responsible for patterns of relations in observed measurements (Plucker & Renzulli, 1999). Although latent variable analysis was unavailable to Wallach and Kogan, modern researchers can reanalyze their data to test their conclusions and to estimate new models that were not considered by Wallach and Kogan. Latent variable analyses can be conducted without access to the full set of raw data. Given sufficient descriptive statistics—means, standard deviations, sample sizes, and a correlation matrix—researchers can reconstruct a covariance matrix for analysis (Kline, 2005).

Wallach and Kogan's research is well-suited for latent variable analysis. First, the researchers collected multiple measures of each construct. Each student completed 10 measures of intelligence and achievement and 10 measures of creativity. The 10 creativity measures can be split into 5 measures of originality and 5 measures of fluency. Second, Wallach and Kogan's sample size ( $n = 151$ ) is sufficient for latent variable analysis. Although a larger sample is always desirable, a sample of 151 suffices if the measured variables relate strongly to the latent variable and if the model has relatively few parameters (see Jackson, 2001, 2003). Moreover, concerns about errors due to small sample sizes can be alleviated by bootstrapping procedures. Third, the study used high-quality measures of creativity and intelligence. The measures of creativity invented by Wallach and Kogan have become classics in the field, and the measures of intelligence and achievement were standard, widely-used measures at that time. Finally, unlike other studies (e.g., Getzels & Jackson, 1962), Wallach and Kogan's measures of creativity and intelligence formed distinct and coherent clusters, which is necessary for modeling them as distinct latent factors.

The present research reanalyzed Wallach and Kogan's data using latent variable analysis. This research had two aims. First, it tested if the relation between creativity and intelligence is still negligible when the data are analyzed with more sophisticated methods. Several factors could have deflated the creativity-intelligence relation in Wallach and Kogan's research. For instance, the creativity tests shared method variance that was not shared with the intelligence tests. Conversely, the measures of intelligence and achievement shared method variance that was not shared with the creativity tests. Furthermore, the low average creativity-intelligence correlation may have been deflated by a few outlying values. A couple of the 10 intelligence measures failed to correlate appreciably with any creativity measure; when correlations are simply averaged, these measures will drag down the average creativity-intelligence relationship. Second, the present research sought to estimate models that were not estimated by Wallach and Kogan. In particular, their data offer a chance to explore the relations of originality and fluency to intelligence and to distinguish between intelligence and academic achievement.

## AN OVERVIEW OF THE ANALYSES

### Measures of Creativity

Five creativity tests were administered. In the *instances* test, children generated instances for four categories (e.g., things that are round). In the *alternate uses* test, children generated uses for eight common objects (e.g., newspaper, knife, cork). In the *similarities* test, children generated ways in which pairs of objects were similar for 10 object pairs (e.g., milk and meat, a train and a tractor). In the *pattern meanings* test, children viewed 8 abstract visual designs and suggested interpretations of the patterns. In the *line meanings* test, children viewed 9 pictures of continuous lines and suggested interpretations of the lines. Each test thus involved between 4 to 10 assessments.

Each of the five tests yielded scores for originality and fluency. Originality was assessed by assigning one point for each response that appeared only once in the sample of 151 children. Thus, original responses were literally unique in the sample. The number of unique responses per test was summed to create an originality score for

that test. Fluency was assessed by the total number of items generated for each test. This fluency measure is uncorrected for originality (cf. Runco & Albert, 1985; Snyder, Mitchell, Bossomaier, & Pallier, 2004), so fluency and originality will be substantially related due to the scoring method.

## Measures of Intelligence

Ten indicators assessed a latent intelligence factor. Three indicators were the vocabulary, picture arrangement, and block design subscales of the Wechsler Intelligence Scale for Children. Two indicators were measures of verbal aptitude and quantitative aptitude provided by the School and College Ability Test (SCAT). Five indicators were measures of school achievement taken from the Sequential Tests of Educational Progress (STEP). In particular, scores were obtained for accomplishment in mathematics, science, social studies, reading, and writing. It is clear to modern researchers that the measures of intelligence overemphasize measures of achievement (STEP) and aptitude (SCAT) at the expense of measures of fluid intelligence and reasoning (cf. Kane et al., 2004). All of the fifth graders (70 boys, 81 girls) in a suburban public school system participated, so a wide range of intelligence scores was likely represented.

## Model Specification

Wallach and Kogan (1965) provided sufficient information to reconstruct a covariance matrix for analysis. The correlations between measures of creativity were taken from Table 7 (p. 46); the correlations between measures of intelligence were taken from Table 8 (p. 47); and the correlations between measures of creativity and intelligence were taken from Table 9 (p. 49). Wallach and Kogan did not provide the overall standard deviations for each measure, but they did report the standard deviations for boys and girls (Tables 17 and 18, p. 57). These standard deviations were pooled to estimate the standard deviation for the overall sample. AMOS 6 (Byrne, 2001) was used to analyze the data. Researchers can download the input file from [http://www.uncg.edu/~p\\_silvia/](http://www.uncg.edu/~p_silvia/).<sup>1</sup>

Three latent variables were modeled; Figure 1 depicts the model. A latent originality factor was defined by the originality scores for the five creativity tests; a latent fluency factor was defined by the fluency scores for the five creativity tests. To account for test-specific method variance, the model allowed the residuals to covary for each creativity test. A latent intelligence factor was defined by all 10 tests of intelligence and achievement.

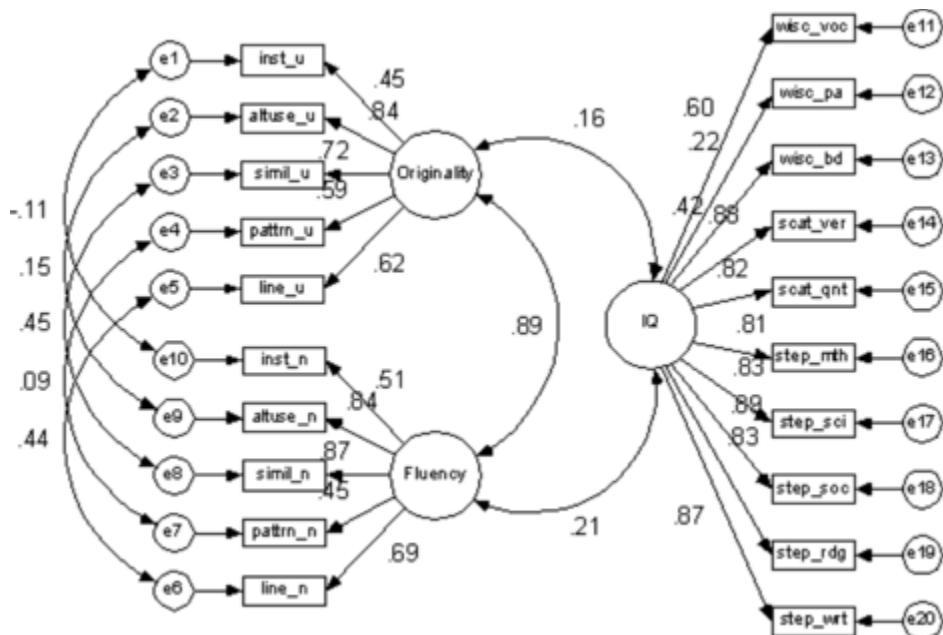


FIGURE 1. Relationships between originality, fluency, and intelligence.

## Assessment of Model Fit

Model fit was assessed using several standard measures (Hu & Bentler, 1999; Kline, 2005). The chi-square test examines the model's badness of fit: a significant chi-square indicates significant deviation between the observed and reproduced covariance matrixes. Because it is widely known that the chi-square test is biased by large samples, one can compute the ratio between the chi-square and the degrees of freedom. Ratios of  $\chi^2/df$  less than 2 indicate good fit (Byrne, 1989). The comparative fit index (CFI) indicates the degree to which the fit of the predicted model improves upon the fit of a null model. CFI values greater than .90 are seen as good (Hu & Bentler, 1999). Finally, the root mean-square error of approximation (RMSEA) is an index that accounts for the complexity of the model. RMSEA values less than .08 indicate good fit, and values less than .05 indicate close fit (Browne & Cudeck, 1993).

## RESULTS

### Originality, Fluency, and Intelligence

How did originality and fluency relate to intelligence? Figure 1 depicts the relations between these variables; the parameter estimates are standardized. The predicted model fit the data well. Although the chi-square test was significant,  $\chi^2(162) = 288, p < .001$ , the ratio of  $\chi^2/df$  was 1.778, which falls below the cut-off of 2. The CFI was greater than .90 (.928), and the RMSEA was less than .08 (.072). Thus, several fit indexes suggested that the predicted model achieved a good fit to the data.

Originality and fluency were highly related,  $\beta = .892, p < .001$ . Originality had a modest and marginally significant relationship with intelligence,  $\beta = .156, p < .098$ ; fluency had a stronger, significant relationship with intelligence,  $\beta = .214, p < .022$ . Thus, the latent originality and fluency factors had stronger relationships with intelligence than the average creativity-intelligence correlation ( $r = .09$ ) reported by Wallach and Kogan (1965).

### Creativity and Intelligence

The high relations between originality and fluency suggest the estimation of a model in which overall creativity predicts intelligence. Indeed, this is the model implied by Wallach and Kogan's (1965) use of average creativity-intelligence correlations. The resulting model, depicted in Figure 2, fit the data well ( $\chi^2/df = 1.895$ , CFI = .917, RMSEA = .077). Creativity and intelligence were significantly and modestly related,  $\beta = .20, p < .045$ .

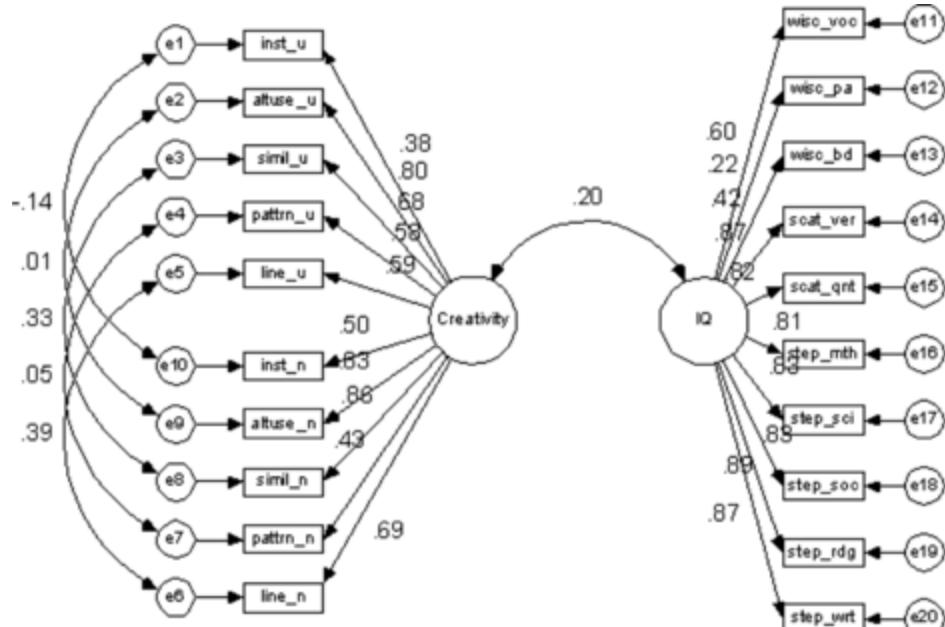


FIGURE 2. Relationship between creativity and intelligence.

As mentioned earlier, the measures of intelligence combined conventional measures of IQ (the Wechsler scales) with measures of academic achievement. Intelligence is obviously important to academic achievement, but it's worth distinguishing between intelligence and achievement. A third model, shown in Figure 3, created a latent

intelligence factor (based on the three Wechsler scores) and a latent achievement factor (based on the STEP and SCAT scores). This model fit the data well ( $\chi^2/df = 1.881$ , CFI = .919, RMSEA = .077). Distinguishing between achievement and intelligence didn't appreciably change the relation between the latent creativity and intelligence factors; creativity predicted intelligence ( $\beta = .22$ ) trivially higher than it predicted academic

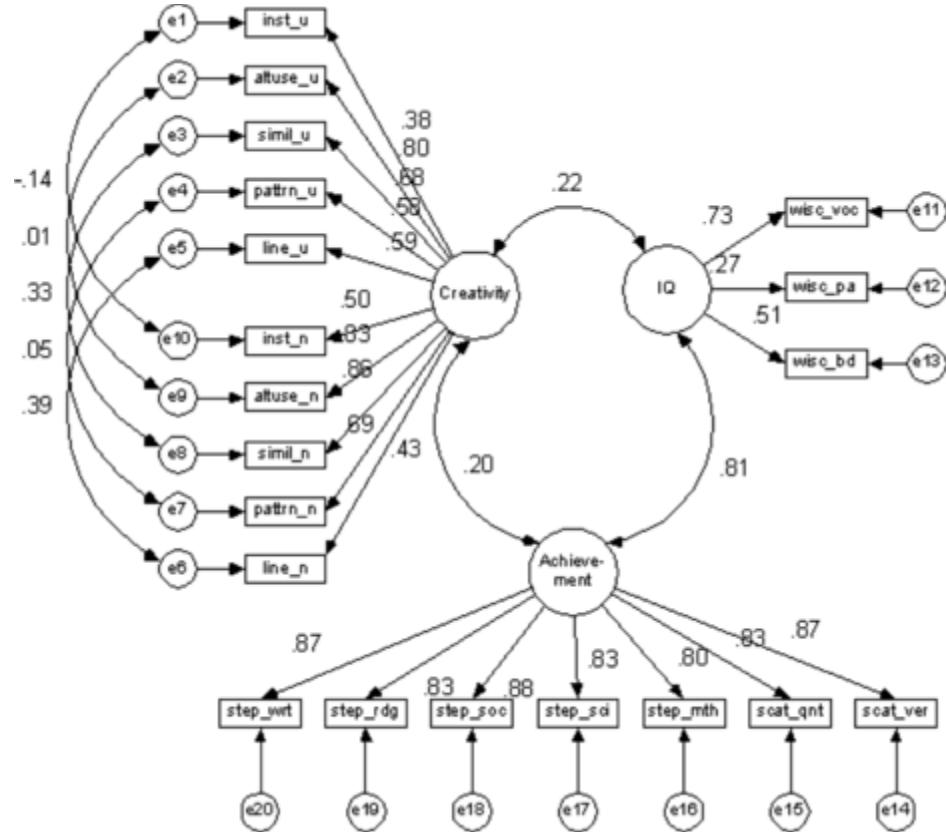


FIGURE 3. Relationship, between creativity, intelligence, and academic achievement.

achievement ( $\beta = .20$ ).<sup>2</sup>

## DISCUSSION

The psychometric approach to creativity has been interested in the relation between creativity and intelligence for over half a century (Guilford, 1950, 1967; Plucker & Renzulli, 1999; Sternberg & O'Hara, 1999). Most studies have found modest relations between creativity and intelligence, but a few studies have found that creativity and intelligence are nearly independent. Wallach and Kogan's (1965) classic study of creativity in children is perhaps the best example of such a study. The present research applied latent variable analysis, a sophisticated approach to multivariate data (Kline, 2005; Loehlin, 2004) that was unavailable to the original researchers, to assess the creativity-intelligence relationship. Latent variable analysis can analyze what is common to classes of tests, control for test-specific method variance, and assess the fit of structural models.

The latent variable analyses revealed that creativity and intelligence were more highly correlated than Wallach and Kogan's (1965) original analyses implied. In Wallach and Kogan's analysis, the average creativity-intelligence correlation was  $r = .09$ . In the present analyses, a latent creativity factor (defined by all 10 creativity scores) significantly predicted a latent intelligence factor (defined by all 10 intelligence and achievement scores). The magnitude of the creativity-intelligence relationship,  $\beta = .20$ , was higher than the average correlation in past research ( $r = .174$ ; Kim, 2005) and higher than the average correlation found in studies that used Wallach and Kogan's scales ( $r = .116$ ; Kim, 2005). It is noteworthy that a latent-variable reanalysis of Torrance's longitudinal data (Plucker, 1999) found a similar effect. A latent divergent thinking factor (indicated by measures of originality, fluency, flexibility, and elaboration) covaried  $\beta = .20$  with a latent intelligence factor (indicated by a single intelligence score).

Future research on creativity and intelligence should exploit the capabilities of latent variable analysis. If creativity and intelligence are viewed as higher-order factors, then they ought to be modeled as latent variables. This requires collecting multiple measures of creativity, such as the class of tests used by Wallach and Kogan (1965), and multiple measures of intelligence. At the same time, Kim's (2005) meta-analysis suggested that researchers interested in the cognitive structure of divergent thinking should look beyond intelligence. Other cognitive factors may be more important for divergent thinking tasks. For example, individual differences in working memory span, the ability to control one's attention (Kane et al., 2004; Süß, Oberauer, Wittman, Wilhelm, & Schulze, 2002), should be important for divergent thinking. People high in working memory span are better at resisting cognitive interference (Kane & Engle, 2003), and success at divergent thinking tasks probably requires overcoming the interference caused by obvious responses and one's prior responses. The modern study of individual differences in cognition offers fertile opportunities for psychometric studies of creativity.

Finally, the present research echoes Plucker's (1999) call for reanalyses of classic studies of creativity. In many cases, it isn't necessary to obtain the full set of raw data. For covariance-based methods like structural equation modeling, the necessary data can usually be extracted from the descriptive statistics provided in the original reports. Modern statistical methods can offer new insights into past research, inform old debates, and inspire new research.

### Acknowledgments

Researchers interested in reanalyzing the Wallach and Kogan (1965) data can download the input file and the AMOS files from [http://www.uncg.edu/~p\\_silvia/](http://www.uncg.edu/~p_silvia/).

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## Notes

<sup>1</sup>This reanalysis can't test the classic threshold model, which proposes a nonlinear relation between creativity and intelligence, because only the covariance matrix, not the raw data, is available. Recent research (Preckel et al., 2006; Sligh, Conners, & Roskos-Ewoldsen, 2005) and Kim's (2005) meta-analysis, however, have found no support for a nonlinear relationship.

<sup>2</sup>Bootstrap estimates were computed for all parameters, using a resampling  $n$  of 1000. Bootstrapping creates new samples by drawing cases from the sample at hand, estimates the model parameters, and provides estimates of relationships and standard errors. If the average estimates from many bootstrap samples resemble the estimates from the original sample, then it's unlikely that the original estimates were biased by deviations from normality or a few outlying values. For the three models, the bootstrapped estimates were essentially the same as the original estimates. Because the raw data were unavailable, Monte Carlo (parametric) bootstrapping was used.