

Is Creativity Domain-Specific? Latent Class Models of Creative Accomplishments and Creative Self-Descriptions

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Is creativity domain-specific? The authors describe the value of latent class analysis for appraising domain generality, and the authors report two studies that explore the latent class structure of creative accomplishments (using Carson, Peterson, and Higgins's Creative Achievement Questionnaire; $n = 749$) and creative self-descriptions (using Kaufman and Baer's Creativity Domain Questionnaire; $n = 3,534$). For creative achievements, clear latent classes were found: the majority of people belonged to an "uncreative" class, and smaller classes were found for visual arts and performing arts. For creative self-descriptions, however, latent classes were not found: people's views of themselves as "creative people" varied quantitatively but not qualitatively. Implications for the assessment and analysis of creativity are considered.

Keywords: creativity, latent class analysis, creative achievement, personality, finite mixture models

Like most of psychology's debates, the debate over whether creativity is domain-specific has many sides. One side argues that creativity is a domain-general trait: people creative in one area are likely to be creative in other areas, just as people high in intelligence perform well on a wide range of cognitive tasks. The domain-general approach, not surprisingly, is associated with the psychometric study of individual differences (e.g., Plucker, 2004, 2005). An opposing side argues that creativity is domain-specific: people have islands of creativity, not a diffuse tendency to be creative. The domain-specific approach is associated with socio-cultural theories (e.g., Sawyer, 2006) and problem-solving theories (e.g., Weisberg, 2006). And, of course, there are many other sides, such as hybrid approaches (e.g., only some traits are domain-general), developmental approaches (e.g., domain-general skills translate into domain-specific accomplishments), nihilistic approaches (e.g., creativity doesn't exist), and trivializing approaches (e.g., who cares about this ancient issue)—the joys of studying creativity are multifarious.

In this article, we used latent class analysis to examine the domain-general nature of creativity. To date, the domain-general versus domain-specific debate has applied statistical models that won't settle the issue. In particular, conventional multivariate models—such as exploratory and confirmatory factor analysis

(CFA)—assume that people vary in amount, not in kind, so these statistical models tacitly favor a domain-general view. We propose that latent class models are more useful. Latent class analysis, in brief, explores whether an observed sample is composed of subgroups (Hagenaars & McCutcheon, 2002). The subgroups, known as latent classes, are exclusive, unordered, and nominal: people belong to only one group, and the groups differ qualitatively.

We applied latent class analysis to two large samples. Our first study examined creative accomplishments; our second study examined creative self-descriptions. Together, the two studies (1) illustrate a new and fruitful methodological tool for the psychology of creativity, and (2) provide an intriguing twist on the general versus specific debate.

A Brief History of the Domain Problem

Within the field of intelligence, there is an enormous debate over the existence of a general factor of intelligence, g , a single factor that is largely responsible for academic performance, among many other things. Some researchers argue strongly for a g factor (Jensen, 1998; Johnson, te Nijenhuis, & Bouchard, 2008); others argue just as strongly against such a factor (Sternberg, Kaufman, & Grigorenko, 2008). Within the field of creativity, the debate is not as contentious, but it has nevertheless provoked a lot of discussion (see Kaufman & Baer, 2005b; Silvia, Winterstein, & Willse, 2008). Indeed, the first point—counterpoint in *Creativity Research Journal's* history was devoted to this topic (Baer, 1998; Plucker, 1998).

Typically, the answer to whether creativity is specific or general depends on the methods used to ask the question (Plucker, 2004, 2005). If a study focused on the creative *product*, then creativity often appears domain-specific (e.g., Baer, 1993). In contrast, if a study focuses on the creative *person*, then creativity often appears

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general. Many of these studies rely on psychometric tests of creativity, such as divergent thinking tests (e.g., Plucker, 1999; Torrance, 1967; Wallach & Kogan, 1965).

Recently, two models have been advanced as a middle ground for domain-specific and domain-general views. Plucker and Beghetto (2004) argue that creativity has both specific and general components. The level of specificity changes with the social context and with development through childhood into adulthood. Another model is the hierarchical Amusement Park Theoretical (APT) model of creativity, which posits general factors that affect creativity in all areas and several levels of domain-specific factors that affect creative performance in increasingly narrow activities (Baer & Kaufman, 2005; Kaufman & Baer, 2005a). These hybrid models are good compromises between the two positions, but they are unlikely to satisfy adherents to strictly domain-specific models (e.g., Sawyer, 2006; Weisberg, 2006). After all, the hybrid theories contend that some traits influence creativity across domains, which is the cardinal point of disagreement.

Testing for Domain-Specificity

How do researchers illustrate domain-specificity? In general, multivariate statistical models are applied to measures of creativity in different domains. One strategy applies exploratory factor analysis. If the domains form a single factor, then creativity appears to be domain-general; if the domains form more than one factor, then creativity appears to be domain-specific. Kaufman and Baer (2004), for example, found that self-descriptions of creativity in 9 domains formed 3 factors (cf. Rawlings & Locarnini, 2007). Similarly, Carson, Peterson, and Higgins (2005) found that the 10 domains of the Creative Achievement Questionnaire formed 2 or 3 factors.

A second strategy applies CFA to the same design: people complete measures of creativity in different domains, and researchers estimate the effect of a higher-order Creativity factor on each domain (e.g., Chen, Himsel, Kasof, Greenberger, & Dmitrieva, 2006; Kaufman, Cole, & Baer, in press; Plucker, 2004). If a higher-order factor predicts each domain, then creativity appears to be domain-general. If not, then additional factors are needed to explain the covariance of the domains.

Multivariate studies are not the only way that researchers have examined the domain-generality problem. For example, some researchers have used transfer designs, in which they train people in a creative domain and then measure transfer to other domains (e.g., Baer, 1996). Nevertheless, the multivariate designs make up most of the research, in part because the logic of the correlational approach is simple and appealing: if creativity is domain-general, then measures of creativity ought to covary.

Three Problems With Correlational Approaches

Lumpy Populations and Clumpy Samples

We see three problems with the correlational approach to testing domain-specificity. First, the statistical models assume that the sample represents a homogeneous population: features of the sample thus should reflect features of the population, provided that the process of sampling did not go awry. Consider a study that measures creativity in writing and creativity in painting. The

researcher wants to know if people who are creative in writing tend to be creative in painting. The zero-order Pearson correlation between creativity in writing and painting estimates the strength of their linear relationship, which in turn is an estimate of the linear relationship in the population. If the r is near zero, then our researcher, like past researchers, would conclude that the study found evidence for domain specificity.

But what if we looked at the cloud of dots in the scatterplot that depicts the small r ? The plot would probably show that some people are high on both writing and painting, many people are low on both variables, and some people are high on only one variable. If there are subsamples in the sample—perhaps small groups of accomplished painters and writers—then the scatterplot will show clumps of outliers. Instead of a scatterplot, we could represent the data with a pie chart that represents the clumps. In the pie chart, for example, most people are low in both domains, some people are high in only one, and a few people are high in both.

A scatterplot depicts a single pattern in a sample; a pie chart depicts exclusive, nominal subgroups in the sample. The question “Are people who are creative in writing also creative in painting?” is thus answered differently. Our scatterplot says “No—people high in one variable are not more or less likely to be high in the other.” Our pie chart, in contrast, says: “It depends—some people are high in both, but most people are not.”

We can see, then, that the null correlation doesn’t settle the matter of domain-specificity. Discrete islands of creative accomplishments will appear as nominal clumps in a sample. If we assume a population is homogeneous, then a statistic like r estimates a feature of the population. But if we do not assume this, then statistics that describe single features are no longer useful.

Factor Structures Are Domain-General

Our second, similar criticism concerns factor structures. Factor analyses of creativity tacitly favor domain-generality—even when they ostensibly show domain-specificity. For example, Carson et al. (2005) reported a 2-factor structure for the Creative Achievement Questionnaire (CAQ). The factor structure characterizes the sample as a whole and, in theory, the homogeneous population from which the sample was drawn. Each participant is a point in the 2-dimensional “Arts” and “Sciences” space: everyone has a score on each factor. As a result, someone low on both factors nevertheless has some level of creativity on each. Even with no achievement in any area, people will be characterized as having a (low) level of creativity in each factor.

The statistical model behind factor analysis ensures that all participants have a value on all factors. In the generalized latent variable modeling framework (Muthén, 2002; Skrondal & Rabe-Hesketh, 2004), an exploratory factor analysis is a kind of latent variable model, in which latent variables (factors) explain the covariance of observed variables (items). The observed variables may have many forms—they can be binary, ordinal, counts, or continuous—but the latent factor itself is continuous and normally distributed: its mean is zero, and its values extend outward to highly extreme (and probably unmeasurable) positive and negative values. As a result, the items may have a floor of zero, but the latent factor extends infinitely into the negative numbers. It is in this sense that factor analysis implies that everyone has some level of creativity. Someone who receives a zero on each creativity item

will have a highly negative score on the latent normal creativity trait, not a zero score. Because the latent trait is continuous, there is, in theory, always some lower trait level, even though that level may not be assessed by the items.

This point is subtle, perhaps, but it is important for understanding what domain-specific creativity should look like empirically. If someone is creative in painting and only in painting, then we would want to characterize her as “creative in the domain of painting,” not as “high in painting, low in science, low in architecture, low in cooking, low in dance, low in music performance, low in creative writing. . .” and so on. Domain-specific creativity appears as nominal clumps. Of note, combining eccentric, nominal groups and factor analyzing their scores will yield a factor structure, but the structure won’t reflect the presence of nominal clumps.

There’s a fun irony to traditional multivariate studies of domain-general. Researchers have argued about whether creativity is general or specific, but all of them have assumed that there is a single, homogeneous population with a single structure of creativity, and that each person has a score on each dimension of creativity. Traditional factor analysis is always domain-general, and the domain-specific camp can’t win if it makes domain-general statistical assumptions.

Absence of Evidence and Evidence of Absence

Finally, the traditional research strategy uses null effects as evidence for domain-specificity. The evidence is thus negative (i.e., an absence of evidence for generality) rather than positive (i.e., evidence in favor of specificity). For example, researchers have concluded that creativity is domain-specific because two measures of creativity correlate weakly. As another example, researchers have argued for domain-specificity based on small path loadings in CFA. When lower-order variables have not loaded highly on a higher-order Creativity variable, then this null effect is seen as evidence for domain-specificity.

Null effects can be a symptom of underlying latent classes, but they can be a symptom of methodological weaknesses, too, such as low power, outliers, restricted range, biased sampling, and gnarled distributions. To add confusion to the matter, some of these problems—particularly clumps of outliers and nonnormal distributions—often indicate underlying latent classes (e.g., Bauer & Curran, 2003). Either way, evidence against generality is not evidence for specificity: researchers advocating domain-specificity must present affirmative evidence for distinct domains.

Creative Domains as Nominal Latent Classes

Psychologists have an awkward relationship with nominal variables: we like to pretend that everything is continuous, perhaps because we learned statistics for interval and ratio data in graduate school. Nevertheless, some things are nominal. Domain-specificity in creativity manifests as nominal subgroups in a sample. When we sample people from a large population, we are catching people from distinct creative subgroups, not from a unitary population. As a result, we must describe the sample in terms of unordered groups instead of quantitative dimensions.

To model creative domains, researchers must relax two related assumptions: (1) that each participant in a sample comes from a

single population, and (2) that only one pattern, structure, or relationship meaningfully describes the sample as a whole. Finite-mixture models, also known as latent-class models, allow researchers to assume that an observed distribution is a mixture of a finite number of smaller distributions (McLachlan & Peel, 2000). Stated differently, researchers can assume that the population is heterogeneous, so sampling from it can yield more than one group.

Latent class analysis is a method for exploring and identifying nominal groups in data (see Hagenars & McCutcheon, 2002; Skrondal & Rabe-Hesketh, 2004). Like exploratory factor analysis, it seeks a simple structural representation of a group of variables. But unlike exploratory factor analysis, it creates a structure of nominal groups, not a structure of continuous dimensions. In latent class analysis, each participant has a probability of belonging to each class. Uncertainty of classification is thus part of the statistical model. In a good class solution, participants have a very high probability of belonging to one class—their most likely class—and near-zero probabilities of belonging to the other classes.

With latent class analysis, researchers can present affirmative evidence for domain-specificity. First, if a simple, one-group model is rejected in favor of a model with distinct latent classes, then researchers can reject “no domains” in favor of “specific domains.” Second, researchers can illuminate the meaning of the classes by including predictors of class membership. If people in creative latent classes are higher in variables that characterize creative people (e.g., openness to experience, creative goals, and training in a creative domain), then the latent classes probably have a meaningful interpretation.

The Present Research

In the present research, we explored the latent class structures of two facets of creativity: creative achievements and creative self-descriptions. In the first study, we looked for nominal groups of creative achievements, as measured by the 10 domains of the CAQ (Carson et al., 2005). In the second study, we looked for nominal groups of creative self-descriptions, as measured by the 7 domains of the Creativity Domain Questionnaire (CDQ; Kaufman, 2006; Kaufman et al., in press).

Study 1: Creative Achievement

Our first study examined the domain-general of creative accomplishments. We used the CAQ, a self-report tool developed by Carson et al. (2005), to assess public creative accomplishments in 10 domains. If creative accomplishment is domain-specific, then we ought to find latent classes associated with different domains.

Method

Participants. We collected a sample of 749 people by combining several samples. Three of the samples consisted of undergraduate students at the University of North Carolina at Greensboro (UNCG). The CAQ was given as part of three studies of divergent thinking: the samples of 79 people and 226 people reported in Experiments 1 and 2 of Silvia, Winterstein, Willse, Barona, et al. (2008), and a sample of 189 people (currently unpublished). The fourth sample consisted of 255 people who took part in a Web-based study of creativity and cognitive styles, based

at Illinois Wesleyan University. It included people from Illinois Wesleyan University (78%), Wittenberg University (16%), and UNCG (6%). The total sample was approximately 27% men and 73% women. Approximately 96% of the people ($n = 714$) spoke English as a native language. We excluded non-native speakers from the analysis, but it didn't substantially change the results.

The CAQ. The CAQ (Carson et al., 2005) measures creative accomplishments in 10 domains: visual arts, music, dance, architectural design, creative writing, humor, inventions, scientific discovery, theater/film, and culinary arts. Each domain is measured with 7 items. Unlike other self-report measures, the CAQ emphasizes concrete and public accomplishments. Table 1, for example, lists the items for the creative writing domain. The first item for each domain is a "no creativity" response: people can indicate that they have no accomplishment in the area. The items then increase in steps toward greater accomplishment, similar to a Guttman scale.

The scoring of the CAQ is clever and unusual. People give a binary *yes* or *no* response to each normal item, but they give a number for each starred item, such as item 7 in the creative writing domain. For normal items, a *yes* response yields points equal to the item number. If someone checks *yes* to items 1, 2, and 3, for example, she receives 6 points (1 for item 1, 2 for item 2, and 3 for item 3). For starred items, the response is multiplied by the item number. If someone reports 4 reviews in national publications, for example, she receives 28 points for that item (4×7). The points are then summed for each domain. In this quasi-Guttman approach, conventional measures of internal consistency are not meaningful.

The CAQ's novel scoring approach yields highly skewed distributions. Each subscale has scores that resemble overdispersed Poisson distributions with excessive zeros (Long, 1997). The modes are typically zero—reflecting a lack of achievement in a domain—and the ranges vary madly. The minimum value is zero, but the maximum value is unknown: the starred items, by multiplying responses, allow extremely high subscale scores. This is not necessarily bad. As Carson et al. (2005) argue, creative accomplishment is skewed: most people have no accomplishments, and few people are highly accomplished.

Results and Discussion

Model specification and estimation. Like SEM, latent class analysis involves choosing starting values for the analysis. Unlike

Table 1
The Creative Writing Subscale From the Creative Achievement Questionnaire (CAQ)

Creative Writing	
_____	0. I do not have training or recognized talent in this area (Skip to next section).
_____	1. I have written an original short work (poem or short story).
_____	2. My work has won an award or prize.
_____	3. I have written an original long work (epic, novel, or play).
_____	4. I have sold my work to a publisher.
_____	5. My work has been printed and sold publicly.
_____	6. My work has been reviewed in local publications.
* _____	7. My work has been reviewed in national publications. (Write number.)

SEM, latent class models have many local solutions on the likelihood surface (Hipp & Bauer, 2006). To avoid local solutions, researchers must try a wide range of starting values. If many different sets of values converge to the same solution, then that solution probably is the global likelihood solution. Mplus 5.1—the software used for the analyses—generates random sets of starting values based on a seed value; the values are then perturbed by a scaling factor. The starting values are iterated to initial solutions, and the best initial solutions are then iterated to final solutions. The final model presented here explored 1,000 random starting values and several seed and perturbation values.

Like choosing the number of factors to retain in an exploratory factor analysis, choosing the number of latent classes is based on statistical guidance, theoretical sensibility, and parsimony. For statistical guidance, researchers can examine (1) entropy, an index of classification quality; (2) a family of likelihood ratio tests (LRTs), which compare models with adjacent numbers of classes (Lo, Mendell, & Rubin, 2001); and (3) information-criteria, such as Akaike's Information Criterion (AIC) and the Bayesian Information Criterion (BIC). The problem of choosing the correct number of classes is a busy area of research (see Bauer & Curran, 2003; Brame, Nagin, & Wasserman, 2006; Nylund, Asparouhov, & Muthén, 2007). To date, the BIC and a bootstrapped LRT appear to perform well (Nylund et al., 2007). Readers should keep in mind that these statistical tools are relative: they provide information about which of two models is better, but researchers may be choosing between two poor models.

Regarding theoretical sensibility and parsimony, we evaluated solutions based on whether the classes made sense, given the domains and the sample of college students. Some classes—for example, a class of students accomplished in architecture, invention, and science—are unlikely, given the achievements possible as a college student. We also preferred solutions with fewer classes and with no tiny classes (e.g., less than 5% of the sample). Simpler solutions with larger groups are more likely to replicate in similar samples. Finally, we can assess the meaning of classes by predicting class membership with other variables. If classes differ in meaningful ways—for example, if creative classes are higher in creative goals, traits, and training—then we can be more confident in the validity of the solution.

As we noted earlier, the 10 domain scores of the CAQ resemble Poisson distributions with too many zeros (Hilbe, 2007; Long, 1997). The 10 domains were estimated as Poisson variables (Skrondal & Rabe-Hesketh, 2004). We used Mplus 5.1 and full-information maximum-likelihood estimation with robust standard errors (MLR) for all models.

Interpreting the Latent Classes. We settled on a solution with three latent classes. Table 2 shows the average class-assignment probabilities, which reflect well-separated classes. For people for whom Class 1 was the most likely class, for example, the chance of belonging to Class 1 was 95.4%, and the chance of belonging to the remaining classes was much lower (1.0% and 3.6%).

Figure 1 depicts the class profiles. The y-axis indicates the level of creative accomplishment in a domain, and the x-axis lists the 10 domains. The largest class (Class 3) had around 66% of the sample. This "No Creativity" class consisted of people with essentially no creative accomplishments, as shown by their near-zero values for each domain. The remaining two classes—each around 17% of the sample—represented two clusters of creative accom-

Table 2
Average Probabilities of Most Likely Class Membership (Row)
by Class (Columns): Study 1

	Class 1	Class 2	Class 3
Class 1	.954	.010	.036
Class 2	.012	.967	.021
Class 3	.011	.007	.982

Note. This class solution is depicted in Figure 1; it has an entropy value of .939.

ishment. One class (Class 1) was a “Visual Arts” class: people in this group reported high accomplishment in only the visual arts domain. Another class (Class 2) was a “Performing Arts” class: people in this group reported high accomplishments in several performing arts—dance, music, theater, and film—and in creative writing.

In this solution, then, we observed domain-specific patterns of creative accomplishment. The presence of a large “No Creativity” group, although depressing to creativity researchers, illustrates that creative accomplishment is atypical: not everyone is pursuing creative goals or training. The “Visual Arts” group represented accomplishment specific to the visual arts. The “Performing Arts” group, in contrast, represented accomplishment specific to several performing arts. This group had broader accomplishments, although all (except writing) involved performing in public.

To appraise the meaningfulness of the class solution, we explored whether individual differences predicted class membership. In particular, we evaluated whether the classes differed in the Big Five factors and in the probability of having a college major related to the arts. To compare the classes, we could assign people to their most likely class and then compare the three classes with a one-way analysis of variance (ANOVA). This method, however, ignores uncertainty associated with class membership. Each person has a probability of belonging to each class, so the class boundaries are fuzzy. Mplus affords a posterior-probability-based multiple

imputation analysis that compares groups while preserving information about classification certainty. Interested readers can consult recent papers for more information (e.g., Silvia, Henson, & Templin, in press; Wang, Brown, & Bandeen-Roche, 2005); uninterested readers can view this analysis as essentially like a one-way ANOVA for our three between-person groups.

Two sets of variables were available across all of our subsamples. First, we had Big Five scores, measured with items from the International Personality Item Pool (Goldberg et al., 2006). Openness to experience consistently predicts creative traits, lifestyles, goals, and accomplishments (Feist, 1998, 2006; Joy, 2004; King, Walker, & Broyles, 1996; McCrae, 1987; Wolfradt & Pretz, 2001), so we would expect openness to predict class membership. Other Big Five variables—particularly extraversion and conscientiousness—have appeared as important in past work, but they have been less widely studied than openness. Second, we had the participants’ college majors, which had been classified into *conventional majors* (a score of 0) and *arts majors* (a score of 1). Classifying majors as creative versus noncreative is crude and controversial (see Baer, 2008), but it is a rough way of classifying people’s career goals (for details, see Silvia, 2007; Silvia, Winterstein, Willse, Barona, et al., 2008).

Several findings suggested that the classes were meaningful. (Table 3 reports the estimated means for the classes and the T3 focused comparisons.) First, people in the Visual Arts class and the Performing Arts class were higher in openness to experience than people in the No Creativity class, $\chi^2(2) = 37.6, p < .001$. Second, people in the Performing Arts class were higher in Extraversion than people in the Visual Arts and No Creativity classes, $\chi^2(2) = 8.15, p = .017$. Finally, the percentage of people who majored in the arts differed significantly across the groups, $\chi^2(2) = 25.6, p < .001$. People in the Visual Arts (34.0%) and Performing Arts (20.1%) classes were more likely than people in the No Creativity class (6.3%) to have an arts major.

Taken together, the differences between classes suggest that our latent class model is meaningful. Relative to the No Creativity class, the two creative classes were higher in openness to experi-

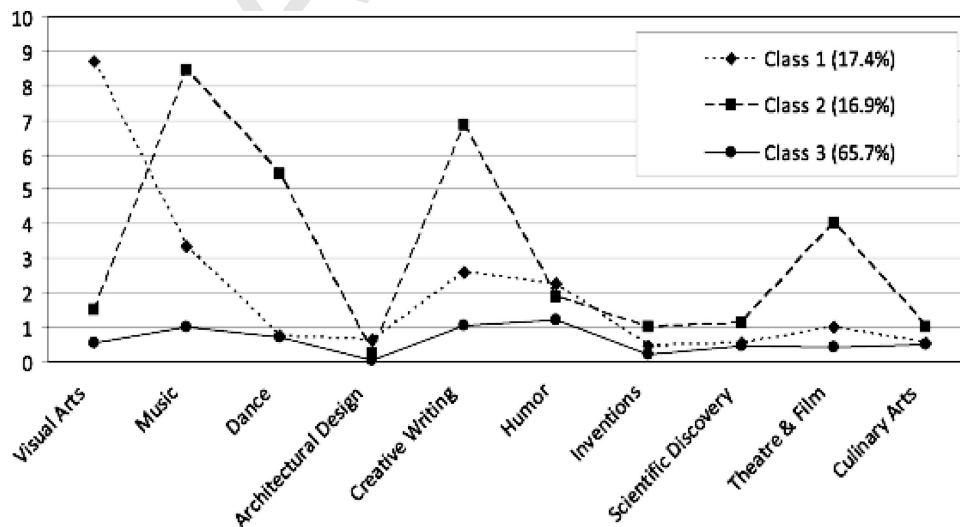


Figure 1. Profiles for a three-class model of creative achievement: Study 1.

Table 3
Individual Differences Across the Three Latent Classes: Study 1

	Class 1 (Visual Arts)	Class 2 (Performing Arts)	Class 3 (None)
Openness to experience	3.73 _a	3.77 _a	3.42 _b
Extraversion	3.35 _a	3.59 _b	3.34 _a
Arts major	.340 _a	.201 _b	.063 _c

Note. The Big Five traits were measured using a 1 to 5 response scale; the values for arts major are proportions. For each row, different subscripts reflect significant between-class differences, $p < .05$.

ence—a hallmark of people with creative goals and interests (Feist, 1998)—and were more likely to be pursuing a degree in the arts. Furthermore, the Performing Arts class was higher in extraversion than the Visual Arts class. Gregariousness is a core feature of extraversion (Fleeson, Malanos, & Achille, 2002), so it's sensible to find that people accomplished in dance, music, and acting are more extraverted than people accomplished in visual art.

Study 2: Creative Self-Descriptions

Are self-descriptions of creativity domain-specific? There are many ways to measure individual differences in creativity. Kaufman (2006) has suggested simply asking people to report their levels of creativity, based on their own definition of creativity, in diverse domains. To date, exploratory and CFA have shown several factors, although the factors vary somewhat (Kaufman, 2006; Kaufman & Baer, 2004; Kaufman et al., in press; Rawlings & Locarnini, 2007). Obviously, asking people to describe their concrete, public accomplishments is different from asking them for global assessments of their creativity. Asking for global self-reports of creativity harnesses people's self-concept of creativity, their theory of what they are like (Epstein, 1973). Analyzing creative self-descriptions thus expands our analysis of creative accomplishments. As before, we explored whether there were nominal groups within the sample.

Participants

We reanalyzed data from a sample of 3,534 people who completed the CDQ. The sample is primarily college students from universities in California, Massachusetts, and New Jersey; other participants include nurses, teachers, high-school students, counselors, psychologists, and customers of a movie theater. For more details about the sample, the CDQ, and prior analyses, readers can consult Kaufman (2006) and Kaufman et al. (in press).

The CDQ. The CDQ measures self-reported creativity in different domains. The instructions ask people "to rate your creativity in the following domains" and "to think about your creativity in each specific domain as you understand it." People rated their creativity for 56 domains on a 6-point Likert scale: *Not at all creative* (1), *Not very creative* (2), *A little creative* (3), *Somewhat creative* (4), *Very creative* (5), and *Extremely creative* (6). A *Not applicable* option was provided; this response was treated as a missing value. The items were single words or phrases, such as *Chemistry*, *Music Composition*, and *Humor/Comedy*.

To contrast the CAQ and the CDQ, we can compare how they assess creativity in writing. The CAQ writing scale, shown in Table 1, lists increasingly uncommon levels of accomplishment. The CDQ presents 4 items related to writing: *English Literature/Criticism*, *Writing Fiction/Prose*, *Writing Nonfiction/Journalism*, and *Writing Poetry*. People simply give a 1–6 rating for each item.

Results and Discussion

Data reduction. The most recent exploratory factor analysis (Kaufman et al., in press) suggested that the 56 items could be represented with 7 domains: entrepreneurial (4 items; $\alpha = .63$), performing arts (8 items; $\alpha = .76$), visual arts (11 items; $\alpha = .79$), math/science (9 items; $\alpha = .79$), problem solving (6 items; $\alpha = .66$), interpersonal (12 items; $\alpha = .78$), and verbal arts (6 items; $\alpha = .76$). We averaged the items within each domain and used the domain averages in the latent class analysis. The domain averages, which approximated normal distributions, were treated as continuous variables.

The approach to model estimation and selection followed the strategy described in Study 1. We estimated models for a wide range of latent classes (ranging from 2 to 7). The final solutions were based on a wide range of random starting values, and they were consistent across random-number seeds and perturbation factors.

Interpreting the latent classes. Did creative self-descriptions form latent classes? We suspect not. First, the entropy values were poor for all of the class solutions: the classes weren't strongly separated. For solutions ranging from 2 to 7 classes, the entropy values ranged from .574 (the 7-class model) to .655 (the 2-class model). As an example of the mushy class structures, Table 4 shows the average class probabilities for the 4-class solution. People's probabilities of class membership favored one class, but not as sharply as in Study 1.

Second, the class profiles suggested quantitative variation in creative self-descriptions, not nominal classes. Figure 2 shows the profiles for the 2-class and 4-class solutions. The classes reflect amount rather than kind. For the 2-class solution, one class is a high class and the other is a low class; for the 4-class solution, the four profiles represent four degrees of endorsement. Unlike the profiles in Study 1, the profile lines do not cross, and each profile has a similar rank-ordering of the seven domains. Even large class solutions, such as 7-class and 12-class solutions, showed essentially quantitative distinctions between the class profiles.

Table 4
Average Probabilities of Most Likely Class Membership (Row) by Class (Columns): Study 2

	Class 1	Class 2	Class 3	Class 4
Class 1	.780	.023	.047	.150
Class 2	.005	.827	.000	.168
Class 3	.166	.000	.833	.001
Class 4	.124	.096	.001	.779

Note. This class solution is depicted in the lower panel of Figure 2; it has an entropy value of .652.

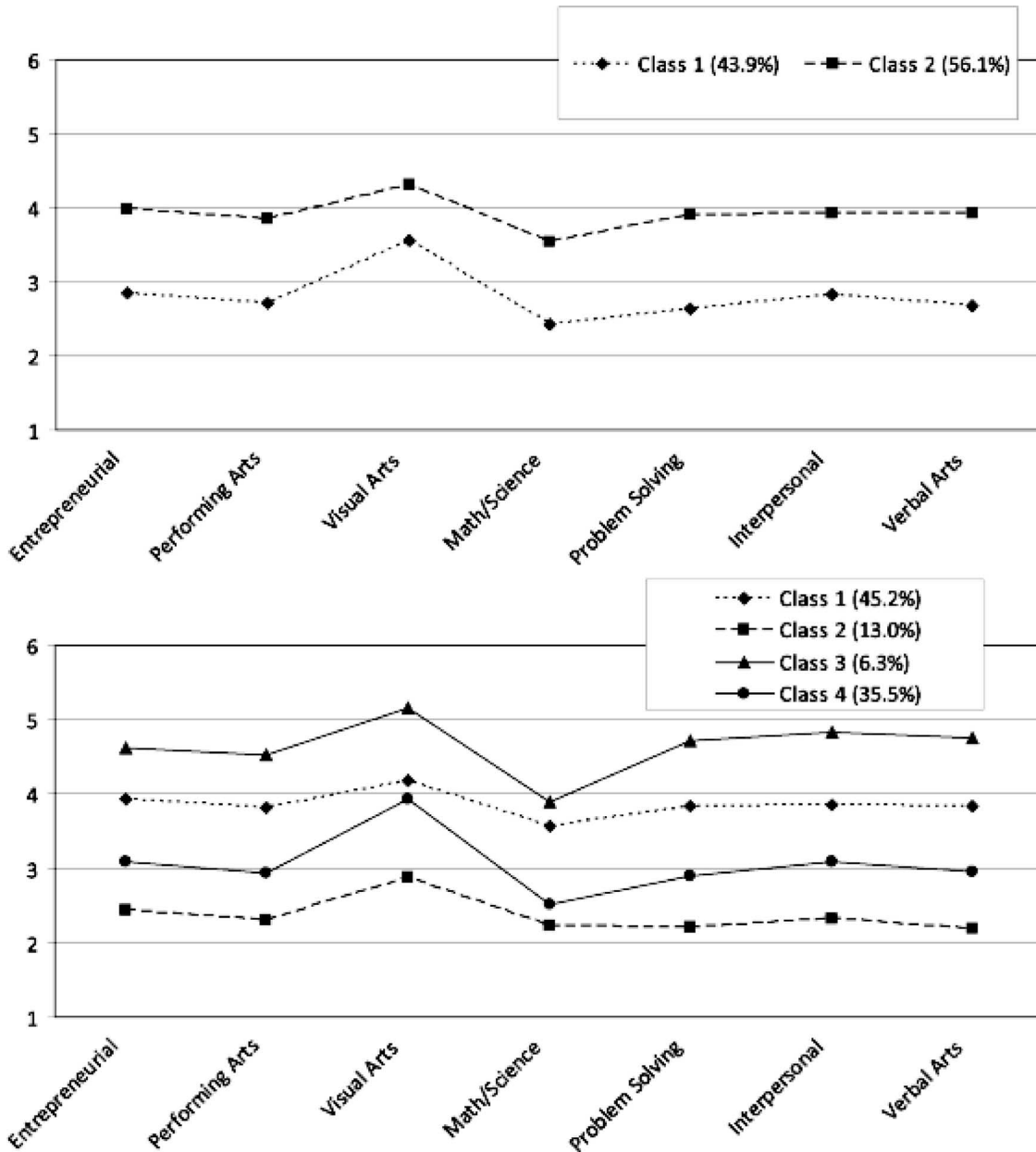


Figure 2. Profiles for two-class and four-class models of creative self-descriptions: Study 2.

In short, creative self-descriptions, as measured by the CDQ, appear to have a factor structure rather than a class structure: people vary in amount, not in kind. Consistent with this conclusion, the seven domains correlate positively, and often highly, with each other. A CFA of a subset of the sample (Kaufman et al., in press) found that most of the domains had a strong higher-order factor, so implicit self-theories of creativity may be domain-general.

General Discussion

Our research offers a twist on the old debate over whether creativity is domain-specific. We have suggested that the typ-

ical methodological strategy—measure dimensions of creativity and then appraise their covariance—won't offer affirmative evidence for domain-specificity. If researchers assume a population is homogeneous, then they are tacitly favoring domain-general. Latent class analysis, in contrast, can identify nominal groups in a sample. These clumps needn't have an ordered, quantitative relation to each other, and they needn't be equal in size. If creativity is domain-specific, then it will appear as clumps of people with similar accomplishments.

Our two studies demonstrate what latent classes look like. In Study 1, we found three latent groups: a Visual Arts class, a Performing Arts class, and a No Creativity class. The classes had

different profiles on the 10 domains (see Figure 1) and different relationships with openness to experience, extraversion, and college majors (see Table 3). This study illustrates the nominal nature of the classes: each participant has a most likely class, the classes make up different proportions of the sample, and the classes have no ordered relation to each other.

In Study 2, we saw what a lack of latent classes can look like. Adding classes expanded the overall sample profile like an accordion: the classes represented quantitative, ordered differences, not nominal groups. Creative self-descriptions thus resemble other variables that are continuous and quantitative, such as individual differences in personality: they are best described with distributions, not with nominal groups.

Are There Domain-General Traits?

One question that our studies can't address is whether there are domain-general creative traits. In the psychometric tradition, researchers have proposed global propensities to be creative. Traits like divergent thinking (Plucker, 1999; Silvia, 2008a, 2008b), creative potential (Runco, 2007), creativity-relevant skills (e.g., tolerance for ambiguity; Amabile, 1996), and ideational abilities (Simonton, 1999) presumably foster creativity across many domains. Most of these theories would agree that domain-general traits translate into domain-specific accomplishments. A trait such as divergent thinking, for example, may enhance creativity in many domains, but the extensive knowledge and training needed for creative work channels the effect of divergent thinking into a specific area of accomplishment.

There is surprisingly little evidence related to the general-to-specific view. Most of the research on divergent thinking and creative accomplishment is cross-sectional, so a skeptic could assert that extensive creative training enhances divergent thinking. Longitudinal studies are needed to illustrate the effect of global traits on specific accomplishments. In Torrance's data, for example, Plucker (1999) found a large effect of childhood divergent thinking on adult creative accomplishment. This kind of design is a good model for future research. Given the likely presence of latent classes of accomplishment, it is important to assess creative accomplishment in a wide range of domains.

Longitudinal studies are ideal, but our research shows a way of exploring how general traits translate into specific accomplishments, using cross-sectional designs. The key is to examine how levels of a trait vary across latent classes of accomplishment. For example, past research has shown that divergent thinking predicts creative accomplishments, both cross-sectionally (Carson et al., 2005; King et al., 1996) and longitudinally (Plucker, 1999). These studies, however, measured accomplishments globally: all domains were combined to create a single accomplishment score. Based on Study 1, we would expect accomplishments to form latent classes. It's possible that divergent thinking has a domain-specific effect: it might predict higher accomplishments in some creative areas (e.g., fine art, creative writing) but not others (e.g., engineering, leadership, medicine), depending on features of the domain and the approach to creativity (Sternberg, Kaufman, & Pretz, 2001).

Study 1 provides a small-scale model of what such findings would look like. Openness to experience appeared to be a domain-general trait: the Visual Arts and Performing Arts classes each had

higher openness scores than the No Creativity class (see Table 3). Extraversion, in contrast, was a domain-specific trait: the Performing Arts class was higher in extraversion than the Visual Arts class and the No Creativity class. These findings are limited—they measured only a handful of traits and only 10 domains—but they show how this strategy can be used in later work. If a creative trait is domain-general, then it will predict membership in a broad range of creative classes relative to a no-creativity class. If a creative trait is domain-specific, then it will predict membership in some creative classes but not in others.

Sampling and Assessment

The present studies illustrate how samples and items influence the results of latent class analysis. A latent class solution obviously depends on the sample's composition. In Study 1, for example, no class had any achievement in the domains of culinary arts, invention, scientific discovery, or architecture. In a sample of undergraduates, it would be surprising to find accomplished cooks, inventors, scientists, and architects. The class solution is thus sample-dependent: it describes the kinds of creative classes we would expect to find in similar samples, not in the universe of all possible samples.

Along the same lines, latent class models will analyze only the aspects of creativity that were measured. The CAQ, for example, lacks items related to textile and apparel design and to interior architecture, which are prominent arts majors at UNCG. There is probably a small "decorative arts" class in the data for Study 1, but this class wasn't identified because of the lack of items.

These caveats highlight a difference between latent class analysis and factor analysis. If the population has nominal creative groups, a broad sample is more likely to identify them. A large, diverse sample, for example, will catch a latent class of textile and apparel designers. In factor analysis, however, the search for a single population structure obscures subgroups in the data, so small classes will appear as clumps of outliers in a large sample. Because a large, diverse sample has a better chance of revealing true latent classes, we can have confidence in the lack of clear classes in Study 2, which had a diverse sample of over 3500 people.

Appraising the CAQ and CDQ

The CAQ and CDQ were published at around the time, and both scales seek to assess creativity across different domains. These scales differ in method—for example, the CAQ's quasi-count approach versus the CDQ's Likert approach—but it's likely that they differ in trait, too. In developing the CAQ, Carson et al. (2005) emphasized public creative behaviors. In developing the CDQ, in contrast, Kaufman and Baer (2004) and Kaufman (2006) emphasized subjective meanings of creativity. To date, research has not compared these research tools. In the present studies, they clearly present different pictures of creativity: the CAQ had clear domains, but the CDQ did not. Stated differently, the CAQ has a latent-class structure, but the CDQ has a factor structure.

The issue of validity is thorny and complex, especially in the assessment of creativity, but the present studies add information to the growing bodies of work on what the CAQ and CDQ measure. Regarding the CAQ, the scale appears to meet its goal of capturing

differences across domains. Researchers may want to develop similar domain scales for the CAQ that assess other domains (e.g., decorative arts) or that carve domains more finely (e.g., distinguishing between poetry, fiction, and literary nonfiction). Regarding the CDQ, the scale appears to capture dimensional individual differences, not creative clusters. In light of the results for the CAQ, it seems clear that the CAQ and CDQ are measuring different things. If the CDQ aspires to capture real achievements, it ought to have revealed latent classes. But if the CDQ aspires to capture individual differences in self-beliefs about creativity, then it has the dimensional, continuous structure that it should have.

It seems important, then, to recognize the differences between actual accomplishments and lay theories of creativity. We should not dismiss people's personal theories, of course. Fritz Heider's (1958) famous notion of *naive psychology* reminds us that understanding people's lay theories of psychological concepts are interesting in their own right. For better or worse, people's lay theories of creativity influence their goals and decisions. Sawyer (2007, 2006), for example, outlines several creativity myths, such as "Children are more creative than adults," "Formal training hinders creativity," and "Individuals are more creative than groups." People who believe these myths are probably less likely to do things that will foster creativity (e.g., Kozbelt, 2005, 2007; Weisberg, 2006), such as seek formal training, invest time in practice, and build domain knowledge.

Affirmative Evidence for Domain-Specificity

We have argued that most studies have used null effects as evidence for domain specificity: if two measures of creativity don't correlate, then no evidence for domain-generalizability is inferred. Although informative, null effects are negative evidence (i.e., a lack evidence for generalizability) instead of positive evidence. The biggest value of latent class analysis, perhaps, is that it can provide positive, affirmative evidence for domain-specificity. In Study 1, for example, we could reject, on statistical grounds, a one-group model in favor of a 3-class model and then show that the classes differed on dimensions relevant to creativity. This is much more compelling than simply showing that several measures of creativity fail to covary.

Future work should explore other approaches to classification. Latent class analysis isn't the only way of classifying people into groups. For example, cluster analysis, a venerable tool, has proven itself useful in recent work on creative types (Ivcevic & Mayer, 2006). Cluster analysis and latent class analysis provide different information about a sample, and they have their virtues. Unlike cluster analysis, latent class models allow the classes to be predictors or outcomes in a broader structural model. Nevertheless, many other classification methods can provide affirmative evidence for domain-specificity, so they deserve more attention in future research.

Conclusion

"There are two kinds of people," according to a weary statistics joke: "People who believe in latent classes, and people who don't." The present research thus has something for everyone, or perhaps nothing for anyone: Study 1 found domain-specific classes of creative accomplishment, and Study 2 found a dimensional struc-

ture of creative self-descriptions. These studies show how latent class analysis can inform and extend the long debate over whether creativity is domain-specific.

References

- Amabile, T. M. (1996). *Creativity in context*. Boulder, CO: Westview.
- Baer, J. (1993). *Creativity and divergent thinking: A task-specific approach*. Hillsdale, NJ: Erlbaum.
- Baer, J. (1996). The effects of task-specific divergent-thinking training. *Journal of Creative Behavior*, 30, 183–187.
- Baer, J. (1998). The case for domain specificity in creativity. *Creativity Research Journal*, 11, 173–177.
- Baer, J. (2008). Divergent thinking tests have problems, but this is not the solution: Comments on "Assessing creativity with divergent thinking tasks: Exploring the reliability and validity of new subjective scoring methods." *Psychology of Aesthetics, Creativity, and the Arts*, 2, 89–92.
- Baer, J., & Kaufman, J. C. (2005). Bridging generality and specificity: The Amusement Park Theoretical (APT) model of creativity. *Roepers Review*, 27, 158–163.
- Bauer, D. J., & Curran, P. J. (2003). Distributional assumptions of growth mixture models: Implications for overextraction of latent trajectory classes. *Psychological Methods*, 8, 338–363.
- Brame, R., Nagin, D. S., & Wasserman, L. (2006). Exploring some analytical characteristics of finite mixture models. *Journal of Quantitative Criminology*, 22, 31–59.
- Carson, S. H., Peterson, J. B., & Higgins, D. M. (2005). Reliability, validity, and factor structure of the Creative Achievement Questionnaire. *Creativity Research Journal*, 17, 37–50.
- Chen, C., Himsel, A., Kasof, J., Greenberger, E., & Dmitrieva, J. (2006). Boundless creativity: Evidence for the domain generality of individual differences in creativity. *Journal of Creative Behavior*, 40, 179–199.
- Epstein, S. (1973). The self-concept revisited: Or a theory of a theory. *American Psychologist*, 28, 404–416.
- Feist, G. J. (1998). A meta-analysis of personality in scientific and artistic creativity. *Personality and Social Psychology Review*, 2, 290–309.
- Feist, G. J. (2006). *The psychology of science and the origins of the scientific mind*. New Haven, CT: Yale University Press.
- Fleeson, W., Malanos, A. B., & Achille, N. M. (2002). An intraindividual process approach to the relationship between extraversion and positive affect: Is acting extraverted as "good" as being extraverted? *Journal of Personality and Social Psychology*, 83, 1409–1422.
- Goldberg, L. R., Johnson, J. A., Eber, H. W., Hogan, R., Ashton, M. C., Cloninger, C. R., & Gough, H. G. (2006). The international personality item pool and the future of public-domain personality assessment. *Journal of Research in Personality*, 40, 84–96.
- Hagenaars, J. A., & McCutcheon, A. L. (Eds.). (2002). *Applied latent class analysis*. Cambridge, United Kingdom: Cambridge University Press.
- Heider, F. (1958). *The psychology of interpersonal relations*. New York: Wiley.
- Hilbe, J. M. (2007). *Negative binomial regression*. New York: Cambridge University Press.
- Hipp, J. R., & Bauer, D. J. (2006). Local solutions in the estimation of growth mixture models. *Psychological Methods*, 11, 36–53.
- Ivcevic, Z., & Mayer, J. D. (2006). Creative types and personality. *Imagination, Cognition, and Personality*, 26, 65–86.
- Jensen, A. R. (1998). *The g factor: The science of mental ability*. Westport, CT: Praeger.
- Johnson, W., te Nijhuis, J., & Bouchard, T. J., Jr. (2008). Still just 1 g: Consistent results from five test batteries. *Intelligence*, 36, 81–95.
- Joy, S. (2004). Innovation motivation: The need to be different. *Creativity Research Journal*, 16, 313–330.
- Kaufman, J. C. (2006). Self-reported differences in creativity by gender and ethnicity. *Journal of Applied Cognitive Psychology*, 20, 1065–1082.

- Kaufman, J. C., & Baer, J. (2004). Sure, I'm creative—But not in mathematics! Self-reported creativity in diverse domains. *Empirical Studies of the Arts*, 22, 143–155.
- Kaufman, J. C., & Baer, J. (2005a). The amusement park theory of creativity. In J. C. Kaufman & J. Baer (Eds.), *Creativity across domains: Faces of the muse*. Mahwah, NJ: Erlbaum.
- Kaufman, J. C., & Baer, J. (Eds.). (2005b). *Creativity across domains: Faces of the muse*. Mahwah, NJ: Erlbaum.
- Kaufman, J. C., Cole, J. C., & Baer, J. (in press). The construct of creativity: A structural model for self-reported creativity ratings. *Journal of Creative Behavior*.
- King, L. A., Walker, L. M., & Broyles, S. J. (1996). Creativity and the five-factor model. *Journal of Research in Personality*, 30, 189–203.
- Kozbelt, A. (2005). Factors affecting aesthetic success and improvement in creativity: A case study of the musical genres of Mozart. *Psychology of Music*, 33, 235–255.
- Kozbelt, A. (2007). A quantitative analysis of Beethoven as self-critic: Implications for psychological theories of musical creativity. *Psychology of Music*, 35, 144–168.
- Lo, Y., Mendell, N., & Rubin, D. (2001). Testing the number of components in a normal mixture. *Biometrika*, 88, 767–778.
- Long, J. S. (1997). *Regression models for categorical and limited dependent variables*. Thousand Oaks, CA: Sage.
- McCrae, R. R. (1987). Creativity, divergent thinking, and openness to experience. *Journal of Personality and Social Psychology*, 52, 1258–1265.
- McLachlan, G., & Peel, D. (2000). *Finite mixture models*. New York: Wiley.
- Muthén, B. (2002). Beyond SEM: General latent variable modeling. *Behaviormetrica*, 29, 81–117.
- Nylund, K. L., Asparouhov, T., & Muthén, B. (2007). Deciding on the number of classes in latent class analysis and growth mixture modeling: A Monte Carlo simulation study. *Structural Equation Modeling*, 14, 535–569.
- Plucker, J. A. (1998). Beware of simple conclusions: The case for the content generality of creativity. *Creativity Research Journal*, 11, 179–182.
- Plucker, J. A. (1999). Is the proof in the pudding? Reanalyses of Torrance's (1958 to present) longitudinal data. *Creativity Research Journal*, 12, 103–114.
- Plucker, J. A. (2004). Generalization of creativity across domains: Examination of the method effect hypothesis. *Journal of Creative Behavior*, 38, 1–12.
- Plucker, J. A. (2005). The (relatively) generalist view of creativity. In J. C. Kaufman & J. Baer (Eds.), *Creativity across domains: Faces of the muse* (pp. 307–312). Mahwah, NJ: Erlbaum.
- Plucker, J. A. & Beghetto, R. A. (2004). Why creativity is domain general, why it looks domain specific, and why the distinction does not matter. In R. J. Sternberg, E. L. Grigorenko, & J. L. Singer (Eds.), *Creativity: From potential to realization* (pp. 153–167). Washington, DC: American Psychological Association.
- Rawlings, D., & Locarmini, A. (2007). Validating the creativity scale for diverse domains using groups of artists and scientists. *Empirical Studies of the Arts*, 25, 163–172.
- Runco, M. A. (2007). *Creativity*. Amsterdam: Elsevier.
- Sawyer, K. (2007). *Group genius: The creative power of collaboration*. New York: Basic Books.
- Sawyer, R. K. (2006). *Explaining creativity: The science of human innovation*. New York: Oxford University Press.
- Silvia, P. J. (2007). Knowledge-based assessment of expertise in the arts: Exploring aesthetic fluency. *Psychology of Aesthetics, Creativity, and the Arts*, 1, 247–249.
- Silvia, P. J. (2008a). Another look at creativity and intelligence: Exploring higher-order models and probable confounds. *Personality and Individual Differences*, 44, 1012–1021.
- Silvia, P. J. (2008b). Creativity and intelligence revisited: A latent variable analysis of Wallach and Kogan. *Creativity Research Journal*, 20, 34–39, 1965.
- Silvia, P. J., Henson, R. A., & Templin, J. L. (in press). Are the sources of interest the same for everyone? Using multilevel mixture models to explore individual differences in appraisal structures. *Cognition and Emotion*.
- Silvia, P. J., Winterstein, B. P., & Willse, J. T. (2008). The madness to our method: Some thoughts on divergent thinking. *Psychology of Aesthetics, Creativity, and the Arts*, 2, 109–114.
- Silvia, P. J., Winterstein, B. P., Willse, J. T., Barona, C. M., Cram, J. T., Hess, K. I., et al. (2008). Assessing creativity with divergent thinking tasks: Exploring the reliability and validity of new subjective scoring methods. *Psychology of Aesthetics, Creativity, and the Arts*, 2, 68–85.
- Simonton, D. K. (1999). *Origins of genius: Darwinian perspectives on creativity*. New York: Oxford University Press.
- Skrondal, A., & Rabe-Hesketh, S. (2004). *Generalized latent variable modeling: Multilevel, longitudinal, and structural equation models*. Boca Raton, FL: Chapman & Hall/CRC.
- Sternberg, R. J., Kaufman, J. C., & Grigorenko, E. L. (2008). *Applied intelligence*. Cambridge, United Kingdom: Cambridge University Press.
- Sternberg, R. J., Kaufman, J. C., & Pretz, J. E. (2001). The propulsion model of creative contributions applied to the arts and letters. *Journal of Creative Behavior*, 35, 75–101.
- Torrance, E. P. (1967). The Minnesota studies of creative behavior: National and international extensions. *Journal of Creative Behavior*, 1, 137–154.
- Wallach, M. A., & Kogan, N. (1965). *Modes of thinking in young children: A study of the creativity–intelligence distinction*. New York: Holt, Rinehart, & Winston.
- Wang, C-P., Brown, C. H., & Bandeen-Roche, K. (2005). Residual diagnostics for growth mixture models: Examining the impact of a preventive intervention on multiple trajectories of aggressive behavior. *Journal of the American Statistical Association*, 100, 1054–1076.
- Weisberg, R. W. (2006). *Creativity: Understanding innovation in problem solving, science, invention, and the arts*. Hoboken, NJ: Wiley.
- Wolfradt, U., & Pretz, J. E. (2001). Individual differences in creativity: Personality, story writing, and hobbies. *European Journal of Personality*, 15, 297–310.

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