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Separation of Performance-Approach and Performance-Avoidance Achievement Goals: A Broader Analysis

Kou Murayama
University of Munich

Andrew J. Elliot
University of Rochester

Shinji Yamagata
Keio University

In the literature on achievement goals, performance-approach goals (striving to do better than others) and performance-avoidance goals (striving to avoid doing worse than others) tend to exhibit a moderate to high correlation, raising questions about whether the 2 goals represent distinct constructs. In the current article, we sought to examine the separability of these 2 goals using a broad factor-analytic approach that attended to issues that have been overlooked or underexamined in prior research. Five studies provided strong evidence for the separation of these 2 goal constructs: Separation was observed not only with exploratory factor analysis across different age groups and countries (Studies 1a and 1b) but also with change analysis (Study 2), ipsative factor analysis (Study 3), within-person analysis (Study 4), and behavioral genetics analysis (Study 5). We conclude by discussing the implications of the present research for the achievement goal literature, as well as the psychological literature in general.

Keywords: achievement goals, performance approach, performance avoidance, within-person analysis, behavioral genetics

For the past 3 decades, achievement goals have received considerable attention in the study of motivation in educational psychology (Kaplan & Maehr, 2007; Meece, Anderman, & Anderman, 2006). Achievement goals represent the purpose of competence-relevant behavior (Maehr, 1989). Early on, researchers distinguished between two types of achievement goals: *mastery* goals that focus on developing competence and task mastery, and *performance* goals that focus on demonstrating competence relative to others (Ames & Ames, 1984; Dweck, 1986; Maehr, 1983; Nicholls, 1984). In the 1990s, Elliot and colleagues (Elliot, 1999; Elliot, McGregor, & Gable, 1999) posited that the way competence is defined (i.e., the standard used to evaluate competence) represents the core of the mastery-performance goal distinction and, importantly, argued for the need to attend to a second competence-based distinction, that of valence (Elliot & Harackiewicz, 1996). Competence may be valenced in terms of whether it is focused on a positive possibility to *approach* (i.e., success) or a negative possibility to *avoid* (i.e., failure). Combining the mastery-performance and approach-avoidance distinctions results in four types of achievement goals (Elliot, 1999; Elliot & McGregor, 2001): mastery approach (focused on attaining objective, intrapersonal competence), performance approach (focused on attaining normative competence), mastery avoidance (focused on avoiding objective, intrapersonal incompetence), and performance avoidance (focused on avoiding normative incompetence). Incorporation of the approach-avoidance distinction, especially with regard to performance-based goals, has stimulated a considerable amount of research in the achievement goal literature and has provided much clarity with regard to the achievement goal nomological network.

Recently, achievement goal researchers have begun to take note of the fact that performance-approach and performance-avoidance goals tend to exhibit a strong positive correlation (Elliot & Murayama, 2008; Pugh, Linnenbrink-Garcia, Koskey, Stewart, & Manzey, 2010; Ross, Shannon, Salisbury-Glennon, & Guarino, 2002; Senko & Harackiewicz, 2005). On the one hand, this correlation is to be expected, because these constructs not only share a competence-based component (i.e., an interpersonal standard of evaluation) but are also commonly (and increasingly) measured with items containing substantial semantic overlap (e.g., "My goal is to perform better than the other students" and "My goal is to avoid performing poorly compared to others"; Elliot & Murayama, 2008). On the other hand, this strong positive correlation may also give room for concern that performance-approach

and performance-avoidance goals may not be differentiated (e.g., Duda, 2005; Murayama, 2003; Roeser, 2004; Roeser, Peck, & Nasir, 2006; Tyson & Ben-Eliyahu, 2008; Urdan, 2004a; Urdan & Mestas, 2006; see also Bong, 2009; Brophy, 2005). Indeed, despite the number of studies that have shown the separation between performance-approach and performance-avoidance goal factors in factor analysis (Baranik, Barron, & Finney, 2007; Conroy, Elliot, & Hofer, 2003; Day, Radosevich, & Chasteen, 2003; Elliot & Church, 1997; Middleton & Midgley, 1997; Midgley et al., 1998; Murayama, Zhou, & Nesbit, 2009; Skaalvik, 1997; VandeWalle, 1997; Zweig & Webster, 2004), these prior factor-analytic studies have been quite narrow in scope (as we discuss below), and therefore it is difficult to offer a strong, empirically based statement on the separation of these goals. The purpose of the current research is to lay out the issues that have been overlooked or underexamined in prior empirical research and to conduct a broader analysis of the factorial separation of performance-approach and performance-avoidance goals.

Issues Regarding the Separation of Performance-Approach and Performance-Avoidance Goals

Potentially Biased Samples

To date, extant studies examining the factor structure of achievement goals have been conducted primarily with undergraduate participants from North America. Researchers have repeatedly argued that the factor structure of constructs can be different in different samples (LaGrange et al., 2008; Van de Vijer & Leung, 1997). Thus, the relative uniformity of the samples in existing work may have led to an incorrect or, at minimum, overstated conclusion about the separation of performance-approach and performance-avoidance goals. Two specific points should be considered in this regard. First, researchers have argued that younger individuals have a relatively limited cognitive capacity that may make it more difficult for them to distinguish between variants of performance-based goals than their more seasoned counterparts (Bong, 2009; Urdan & Mestas, 2006). Second, some available data suggest that the positive association between performance-approach and performance-avoidance goals may be higher in Japanese than in North American samples (Murayama, 2003; Murayama et al., 2009). Thus, it is possible that the separation of performance-approach and performance-avoidance goals may not be observed with younger and/or Japanese participants.

Primary Reliance on Confirmatory Factor Analysis (CFA)

Most factor-analytic work on achievement goals has used CFA rather than exploratory factor analysis (EFA). Research in other literatures has shown that discrepant results sometimes emerge from CFA and EFA (e.g., Church & Burke, 1994; Hopwood & Donnellan, 2010; McCrae, Zonderman, Costa, Bond, & Paunonen, 1996; Van Prooijen & Van Der Kloot, 2001; see also Marsh et al., 2009), sparking a heated debate on the pros and cons of each type of analysis. We view CFA and EFA as complementary rather competing (Fabrigar, Wegener, MacCallum, & Strahan, 1999; A. E. Hurley et al., 1997), each having different strengths and weaknesses. A strength of EFA is that it is a data-driven technique that is sensitive to detecting cross-loadings that may be suppressed in CFA (Church & Burke, 1994; Hopwood & Donnellan, 2010; McCrae et al., 1996). Given the high correlation often found between performance-approach and performance avoidance goals, it is possible that some items may have cross-loadings, or even that a single-factor model may be obtained when EFA is used.

Ignoring Change in Goals

All previous research examining the structure of achievement goals has used one-time, cross-sectional (or cohort) data in which respondents rate items with regard to one particular time frame. A limitation of this approach is that it ignores the issue of change in achievement goal pursuit. Goals represent cognitive-dynamic forms of self-regulation (Elliot, 1999), and adaptive self-regulation entails monitoring and adjusting goal pursuit in response to feedback and environmental affordances (Wrosch, Scheier, Miller, Schulz, & Carver, 2003; Zimmerman, 1989). Accordingly, change across time-points in performance-approach and performance-avoidance goal pursuit is expected, and, in fact, investigators are beginning to assess goals across multiple time-points in their research (see L. H. Anderman & Anderman, 1999; Fryer & Elliot, 2007; Middleton, Kaplan, & Midgley, 2004; Senko & Harackiewicz, 2005; Shim, Ryan, & Anderson, 2008). Importantly, this research rests on the implicit assumption that the structure of goal change (e.g., difference scores, residual scores, or slopes) corresponds to the structure observed in cross-sectional data. However, this assumption has yet to be examined, and it remains possible that separation between performance-approach and performance-avoidance goals may be observed in cross-sectional, but not change, data (for relevant work on another construct, see Bardi, Lee, Hofmann-Towfigh, & Soutar, 2009).

Possible Existence of Response Bias

The similar wording of performance-approach and performance-avoidance goal items may introduce an assortment of response biases, such as acquiescence and item context effects (see Urdan & Mestas, 2006, for a similar point). These types of response biases are known to inflate correlations among variables (Knowles, 1988; P. Podsakoff, MacKenzie, Lee, & Podsakoff, 2003; Sudman, Bradburn, & Schwarz, 1996), and, accordingly, the correlation between performance-approach and performance-avoidance goals may actually be an overestimate of true values. Elliot and Murayama (2008) conducted a series of CFAs that controlled for socially desirable responding in achievement goal reports (using Paulhus's, 1991, Balanced Inventory of Desirable Responding and the Marlowe–Crowne Social Desirability Scale; Crowne & Marlowe, 1960). However, these social desirability scales may not be sensitive to the response bias caused by semantic overlap in performance-approach and performance-avoidance goal items. As such, research attending more directly to the issue of semantic overlap may provide a more intricate analysis of the interrelation among the two goal constructs.

Ignoring Within-Person Analysis

Concern about the separation of performance-approach and performance-avoidance goals has sometimes been voiced in the lan-

guage of within-person processes (e.g., "If I want to demonstrate my superior ability, then I implicitly also want to avoid demonstrating my inferior ability"; Roeser, 2004, p. 285). Despite the importance of this concern, however, consistent with the general trend in psychological research, empirical work on the structure of achievement goals (including research on achievement goal change) has relied almost exclusively on a between-person level of analysis. Within-person covariation focuses on dynamic variation within individuals across time-points or situations (Borsboom, Mellenbergh, & van Heerden, 2003; Molenaar & Campbell, 2009; Nesselroade, Gerstorf, Hardy, & Ram, 2007); it is typically examined by collecting repeated measurements of items and computing the covariance of the obtained scores using time-points or situations as the unit of analysis. Importantly, between-person and within-person data are conceptually and mathematically independent, and analyses based on these different types of data can produce very different results (e.g., Borkenau & Ostendorf, 1998; Hamaker, Dolan, & Molenaar, 2005; Hooker, Nesselroade, Nesselroade, & Lerner, 1987). Thus, investigating the separation of performance-approach and performance-avoidance goals based on within-person data promises to yield additional insight into the relation between these constructs.

Ignoring Genetic Versus Environmental Effects

All existing research on achievement goals has focused on observable or self-reported motivational characteristics—phenotypes. Performance-approach and performance-avoidance goals are presumed to be rooted in different biologically based sources (e.g., temperament; Elliot & Thrash, 2002) and activated by different environmental cues (e.g., task framing; Cury, Elliot, Sarrazin, Da Fonseca, & Rufo, 2002). By collecting data from monozygotic and dizygotic twins, behavioral genetic techniques can be used to parse phenotypic variation into genetic and environmental categories (Neale & Cardon, 1992), thereby allowing investigation of the separation of performance-approach and performance-avoidance goals at the level of genetic and environmental effects. Quite different genetic and/or environmental factor structures may underlie observed phenotypic responses (Ando et al., 2004; Jang, Livesley, Angleitner, Riemann, & Vernon, 2002;

Kremen et al., 2009; Yamagata et al., 2006). Thus, examination of the genetic and environmental sources of performance-approach and performance-avoidance goals should provide valuable information about the separation of the two constructs.

Overview of the Present Research

In the present research, we conducted five studies on the separation of performance-approach and performance-avoidance goals, each of which focused on one or more of the aforementioned issues. In Study 1 (1a and 1b), we examined separation while attending to the sample bias and CFA–EFA issues. Study 1a used participant reports of goal pursuit, whereas Study 1b used Monte Carlo computer simulation. Study 2 assessed performance-approach and performance-avoidance goals at two time-points and examined whether change in the two goals showed separation. In Study 3, we addressed the response bias issue by using a paired-comparison method combined with ipsative factor analysis. In Study 4, we had participants report their performance-approach and performance-avoidance goals with regard to five situations and examined whether the two goals were distinguishable based on a within-person analysis. In Study 5, we collected twin data and conducted univariate and multivariate behavioral genetics analyses to investigate the genetic and/or environmental separation of performance-approach and performance-avoidance goals. The descriptive statistics for performance-approach and performance-avoidance goals (along with the correlation between the two goals) for each of the five studies in the present research are provided in Table 1.

Study 1a

In Study 1a, we conducted EFAs on performance-approach goal and performance-avoidance goal items using cross-sectional samples from different age groups (university students and junior high school students) and countries (United States and Japan). We compared a single-factor model with a two-factor model to determine whether performance-approach and performance-avoidance goals are separable based on standard between-person covariation.

Table 1
Descriptive Statistics and the Correlation of Performance-Approach and Performance-Avoidance Goals in Studies 1–5

Study	Performance-approach goals			Performance-avoidance goals			Correlation between the goals
	M	*SD*	Observed range	*M*	*SD*	Observed range	
1: U.S. university	3.80	0.95	1.00–5.00	3.59	1.06	1.00–5.00	0.66
1: Japanese university	3.13	1.21	1.00–5.00	3.14	1.16	1.00–5.00	0.66
1: U.S. junior high	3.39	0.85	1.00–5.00	3.34	0.88	1.00–5.00	0.57
1: Japanese junior high	3.42	0.93	1.00–5.00	3.58	0.90	1.00–5.00	0.69
2: U.S. university[a]	−0.17	0.78	−3.00–2.00	−0.21	0.78	−3.00–2.00	0.58
2: Japanese junior high[a]	−0.24	0.80	−2.67–3.33	−0.55	0.95	−3.33–2.33	0.49
3	2.62	0.94	1.00–4.00	2.38	0.94	1.00–4.00	−1.00[d]
4[b]	3.07	1.27	1.00–5.00	2.83	1.34	1.00–5.00	0.73[e]
5[c]	3.72	1.35	1.00–6.00	3.65	1.19	1.00–6.00	0.55

Note. In all the studies, scale scores were computed by averaging the item scores for each subscale.
[a] Scale change scores from the first assessment to the second assessment. [b] Pooled scores from all five situations. [c] Scores from all the individuals, both monozygotic and dizygotic twins. [d] Due to the mathematical constraints of ipsative scores, the correlation always corresponds to −1. [e] Correlation based on pooled scores from all five situations after adjusting person-level means (centering within persons).

We also conducted multigroup CFAs to directly test the invariance of the factor structure across age groups and countries.

Method

Participants and procedure. Four samples were obtained: 248 U.S. university students (73 men and 175 women; 170 Caucasian, 8 African American, 47 Asian American, 13 Hispanic, and 10 others; mean age = 19.18 years), 99 Japanese university students (36 men and 63 women; mean age = 19.54 years), 128 U.S. junior high school students (76 boys and 52 girls; 119 Caucasian, 4 African American, 2 Asian American, 3 Hispanic; mean age = 13.54 years), and 138 Japanese junior high school students (75 boys and 63 girls; mean age = 12.11 years). Participants completed a questionnaire assessing their current achievement goals for school (U.S. junior high sample), their class (U.S. university sample, Japanese junior high sample), or a specific examination within the class (Japanese university sample).

Performance-approach and performance-avoidance goal scales. For the U.S. university sample, performance-approach and performance-avoidance goals were assessed with Elliot and Murayama's (2008) Achievement Goal Questionnaire–Revised (AGQ-R). The three performance-approach goal items focus on the degree to which respondents are trying to do better than other students (e.g., "My aim is to perform well relative to other students"), whereas the three performance-avoidance goal items focus on the degree to which they are trying to avoid doing poorly relative to other students ("My aim is to avoid doing worse than other students"). Participants responded on a scale of 1 (*strongly disagree*) to 5 (*strongly agree*). For the Japanese samples, a translated version of the AGQ-R was used. The items were translated from English to Japanese, and then back-translated. For the Japanese junior high sample, some translated items were slightly altered to ensure comprehension. For the U.S. junior high sample, the two goals were assessed with items similar to those in the AGQ-R (e.g., for performance-approach: "It is important for me to do well compared to others in school"; for performance-avoidance: "I just want to avoid doing poorly in school compared to others"). In all samples, the wordings of the performance-approach and corresponding performance-avoidance goal items were closely

matched, leading to a stringent test of construct separation. However, it should also be noted that we used preexisting data sets for this study, so there are slight differences in how the goals were assessed across samples.

Results and Discussion

EFA. The most popular approach to determining the number of factors yielded by EFA is the Guttman–Kaiser criterion. In this approach, eigenvalues for the correlation matrix are computed and the number of eigenvalues greater than 1.0 is thought to represent the optimal number of factors for the data set (Guttman, 1954; Kaiser, 1960). Although the Guttman–Kaiser criterion has been widely used in psychological research, it has been soundly criticized (Cattell & Vogelmann, 1977; Fabrigar et al., 1999; Horn, 1965; Humphreys & Ilgen, 1969); indeed, Fabrigar et al. (1999) have stated, "We know of no study of this rule that shows it to work well" (p. 278). Accordingly, we supplemented the Guttman–Kaiser criterion with model fit statistics to determine the appropriate number of factors. Model fit statistics evaluate the fit of the EFA model to the observed data. These statistics are typically used in CFA, but the use of maximum likelihood (ML) estimation allows computation of a variety of model fit indices in EFA as well. In this approach, fit indices are examined in models that assume a different number of factors, and the number of factors is determined based on the model that indicates acceptable fit. We used the following indices to evaluate the adequacy of model fit: comparative fit index (CFI) $\geq$ .90, Tucker–Lewis index (TLI) $\geq$ .90, and root-mean-square error of approximation (RMSEA) $\leq$ .08. The Akaike information criterion (AIC) was also used to evaluate the relative fit of the different models; the lower the values, the better the fit.

EFA with ML estimation (ML extraction) was conducted on each sample twice, once assuming a single-factor model and again assuming a two-factor model. Table 2 presents the first and second eigenvalues, as well as the obtained fit indices from the analyses. The results strongly supported the two-factor model. The two-factor model fit the data well for all samples (see Table 2): $\chi^2(4) = 1.07–4.24$, $ps > .37$, CFI = 1.00–1.00, TLI = 1.00–1.03, RMSEA = .000–.015. On the other hand, the single-factor model

Table 2

Study 1a: Eigenvalues and Fit Indices From Exploratory Factor Analysis Models

Sample	Eigenvalues	χ^2	df	CFI	TLI	RMSEA	AIC
U.S. university							
Single-factor model	4.21	246.24	9	.80	.66	.326	3573.69
Two-factor model	0.88	4.24	4	1.00	1.00	.015	3341.69
Japanese university							
Single-factor model	3.98	124.85	9	.73	.55	.361	1320.34
Two-factor model	1.10	1.07	4	1.00	1.03	.000	1206.56
U.S. junior high							
Single-factor model	3.85	62.31	9	.88	.80	.215	2286.37
Two-factor model	0.82	1.69	4	1.00	1.02	.009	2235.75
Japanese junior high							
Single-factor model	3.91	38.18	9	.93	.89	.153	1987.95
Two-factor model	0.73	3.16	4	1.00	1.01	.000	1962.93

Note. For each sample, eigenvalues in the upper row represent the first eigenvalue; eigenvalues in the lower row represent the second eigenvalue. CFI = comparative fit index; TLI = Tucker–Lewis index; RMSEA = root-mean-square error of approximation; AIC = Akaike information criterion.

was a poor fit to the data for all samples: $\chi^2(9) = 38.17\text{--}246.24$, $ps < .01$, CFI = .73–.93, TLI = .55–.89, RMSEA = .153–.361. Moreover, the AIC favored the two-factor model for all samples. These results indicate that performance-approach and performance-avoidance goals are empirically separable. Interestingly, the one notable exception is the pattern of results based on the Guttman–Kaiser criterion. In three out of four samples, the Guttman–Kaiser criterion suggested a single-factor solution, as the second eigenvalue in these samples dropped below unity (see Table 2). This illustrates the importance of attending to information other than the heavily critiqued Guttman–Kaiser criterion to judge the number of factors in a data set. We also examined the percentage of variance explained by successive factors (Pett, Lackey, & Sullivan, 2003). In all the samples, the first factor explained a large portion of variance (57.2%–66.4%), but the contribution of the second factor was also substantial (6.3%–14.8%).

Table 3 presents promax (a version of oblique factor rotation) factor loadings and factor correlations for the two-factor model for each sample. The results provided additional support for the two-factor model. All variables loaded above .50 on their primary factor and none of the secondary loadings exceeded .30, suggesting a simple two-factor structure.

Multigroup CFA. To further test the two-factor structure, we performed a series of multigroup CFAs. Specifically, we examined the equivalence of the two-factor model across samples by imposing equivalence constraints at each of several increasingly stringent levels (Steenkamp & Baumgartner, 1998; Vandenberg & Lance, 2000). The U.S. junior high sample was excluded from these analyses, because participants in that sample responded to items that were different from those used in the other samples (i.e., we cannot match the items used in this sample with the ones in the other samples).

Three nested models were tested sequentially: a configural invariance model, a metric invariance model, and a (factor) variance–covariance invariance model. In the configural invariance model, the same hypothesized pattern of fixed and free factor loadings (i.e., the items for each goal load only on their respective latent factor) was specified across samples (Steenkamp & Baumgartner, 1998). In the metric invariance model, the matrix of factor pattern coefficients was constrained to be identical across samples.

This implies that common factors have the same meaning across samples, as reflected in invariant factor loadings. In the variance–covariance invariance model, in addition to the equality constraints on the factor loadings, factor variances and covariances were set to be equal across samples. Support for this model would indicate that the factor correlation is the same across samples. Measurement invariance analyses are typically evaluated by change in fit as well as by absolute value of fit. Following G. W. Cheung and Rensvold (2002) and Little (1997), we regard change in CFI (ΔCFI) $\leq .01$ and change in TLI (ΔTLI) $\leq .02$ as supportive of the more stringent model.

The results summarized in Table 4 clearly supported not only the configural and metric invariance models but also the most constrained variance–covariance invariance model, with good absolute fit, $\chi^2(43) = 46.18$, $p = .17$, CFI = 1.00, TLI = .99, RMSEA = .020, as well as good change in fit (ΔCFI = .004, ΔTLI = .006). The factor loadings were also highly significant (ranging from .82 to .93). These results indicate not only that the two-factor structure is invariant across samples but also that the factor loadings and factor correlations are equivalent across samples. The disattenuated factor correlation was .72.

In sum, Study 1a provided strong evidence for the separation of performance-approach and performance-avoidance goals in EFA across different age groups (university and junior high school students) and countries (United States and Japan), as evidenced by good model fit and no cross-loadings. In addition, multigroup CFAs showed not only the common two-factor structure but also the equivalence of factor loadings and factor correlations across samples. Although minor differences in item wording across samples may make strict comparison of results difficult, the fact that the same findings emerged across these data sets may be considered particularly impressive.

Study 1b

In Study 1b, we aimed to augment the EFA results in Study 1a using a computer simulation technique. An issue raised in Study 1a is that there was a discrepancy between the model fit indices and the Guttman–Kaiser criterion, with the former favoring the two-factor model and the latter (mostly) favoring the single-factor

Table 3

Study 1a: Factor Loadings and Factor Correlations From Exploratory Factor Analysis Models

Sample	Item 1	Item 2	Item 3	Item 4	Item 5	Item 6	Factor correlation
U.S. university							
Factor 1	**0.866**	**0.869**	**0.806**	0.164	−0.030	0.090	.64
Factor 2	0.036	0.042	0.091	**0.696**	**0.901**	**0.874**	
Japanese university							
Factor 1	**0.842**	**0.861**	**0.853**	−0.023	0.032	0.124	.56
Factor 2	0.011	0.086	0.031	**0.830**	**0.859**	**0.856**	
U.S. junior high							
Factor 1	**0.713**	**1.035**	**0.551**	0.180	0.068	−0.118	.69
Factor 2	0.174	−0.103	0.273	**0.696**	**0.535**	**0.991**	
Japanese junior high							
Factor 1	**0.709**	**0.646**	**0.834**	0.048	0.161	0.076	.69
Factor 2	0.055	0.140	0.121	**0.713**	**0.702**	**0.783**	

Note. Loadings greater than .40 in absolute magnitude are in bold. Items 1–3 are the items assessing performance-approach goals, and Items 4–6 are the items assessing performance-avoidance goals.

Table 4
Study 1a: Model Testing in Multigroup Confirmatory Factor Analysis

Model	χ^2	df	CFI	TLI	RMSEA	$\Delta\chi^2$	ΔCFI	ΔTLI
Configural invariance	22.12	24	1.00	1.00	.000			
Metric invariance	32.68	32	1.00	1.00	.006	10.57	.000	.003
Variance–covariance invariance	46.18	38	1.00	0.99	.020	13.49	.004	.006

Note. CFI = comparative fit index; TLI = Tucker–Lewis index; RMSEA = root-mean-square error of approximation; $\Delta\chi^2$ = change in chi-square; ΔCFI = change in comparative fit index; ΔTLI = change in Tucker–Lewis index.

model. As previously stated, much research has revealed that the Guttman–Kaiser criterion does a poor job of selecting the number of factors in a data set (Cattell & Vogelmann, 1977; Zwick & Velicer, 1986); however, we are not aware of any studies that have directly compared the fit index and Guttman–Kaiser approaches to factor selection in the case of highly correlated factors. To address this issue, we ran Monte Carlo simulations that directly compared the two approaches. Specifically, we repeatedly applied EFA to simulated data generated from a model that designated a moderate to high factor correlation and evaluated the obtained fit indices and eigenvalues. We also manipulated other parameters (i.e., factor loadings and sample size) to examine the applicability of our findings to other situations.

Method

Simulation design.   The data generation model was a two-factor model with three indicator variables for each factor (analogous to using the AGQ-R). Factor variances were set to 1.0. Three parameters were manipulated: factor correlation, factor loadings, and sample size. The factor correlation was set to .50 (moderate), .65 (high), or .80 (very high) under the multivariate normality assumption. The six factor loadings λ were uniformly fixed at either .55 (low), .70 (moderate), or .85 (high), and the error variances were set to $1 - \lambda^2$, so that the standardized factor loadings were equal to the unstandardized factor loadings. The six error variables were assumed to be independent of one another and normally distributed. These standardized factor loadings are equivalent to Cronbach's alphas of .57, .74, and .89, respectively. The three levels of sample size (N) were 100 (small), 200 (medium), and 400 (large).

Data generation and model fit.   A raw data matrix (N rows by six columns) was generated 500 times for each combination of the 3 (factor correlation) $\times$ 3 (factor loadings) $\times$ 3 (sample size) factors described above. EFA with ML estimation was applied to each data matrix twice, once assuming a single-factor model and again assuming a two-factor model. Fit indices (CFI, TLI, RMSEA, and AIC) were computed for each model. Eigenvalues for each correlation matrix were also calculated. The simulation was performed by a combinational use of R (Version 2.8.1) and faccon.exe (Hattori, 2003).

Results and Discussion

For space considerations, only the results for the conditions $r =$ .50, .65, or .80 combined with λ = .55 or .85 and N = 200 are presented in Table 5; these results highlight the most important characteristics of the overall results.[1] The table contains informa-

tion regarding the means and standard deviations of chi-square statistics, CFAs, TLIs, and RMSEAs out of 500 replications. In addition, the number of supported models based on the Guttman–Kaiser criterion and AIC, as well as the number of improper solutions encountered for each model, is presented. That is, we determined the appropriate number of factors based on the Guttman–Kaiser criterion and AIC for each simulated data set and counted how many times (out of 500 simulations) each model (i.e., the single-factor model and the two-factor model) was supported. When an improper solution was obtained, we did not compare the models based on the AIC. The Guttman–Kaiser criterion occasionally suggested a three-factor model, and in this case, we counted neither of the models.

Of primary interest are the simulation results where the manipulated parameters were close to the parameter estimates obtained in Study 1a. This "typical" situation is seen in the condition with a very high factor correlation ($r = .80$), high factor loadings ($\lambda = .85$), and medium sample size ($N = 200$). The results indicated that the model fit indices (CFI, TLI, RMSEA, and AIC) correctly identified the true (i.e., two-factor) model: The two-factor model showed a good fit to the data (mean CFI = 1.00, mean TLI = 1.00, and mean RMSEA = .022), and the single-factor model showed a poor fit (mean CFI = .89, mean TLI = .83, and mean RMSEA = .213). Interestingly, the Guttman–Kaiser criterion always (500 times out of 500 replications) supported the single-factor model (an incorrect model). This pattern of findings did not change as a function of sample size. On the basis of these observations, it is clear that it is best to rely on fit indices, rather than the Guttman–Kaiser criterion, to determine the number of factors with the AGQ-R data.

Another interesting finding emerged when the true model had low factor loadings ($\lambda = .55$). In this case, even the model fit indices were less able to distinguish between the two models, particularly when the factor correlation was high. For example, when the factor correlation was very high ($r = .80$), the fit indices of the single-factor model were within the range of acceptable fit (mean CFI = .96, mean TLI = .95, and mean RMSEA = .043). These findings suggest that it is critical to have an internally consistent set of items if one wants to test the separability of similar constructs. On an intuitive level, this finding seems reasonable. In the context of a typical personality assessment, low

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[1] The full table is available from the authors upon request. The relative superiority of the fit indices does not change as a function of sample size, but the overall performance in fit indices decreases as the sample size becomes smaller. The pattern of results for λ = .70 is in between the results for λ = .55 and λ = .85.

Table 5
Study 1b: Simulation Results (N = 200)

Model	G–K decision	χ^2 M	SD	df	CFI M	SD	TLI M	SD	RMSEA M	SD	AIC decision	No. improper
					r = .50							
λ = .55												
Single-factor model	9	29.8	10.0	9	.82	.08	.70	.13	.104	.027	7	1
Two-factor model	0	3.6	2.3	4	.99	.01	1.02	0.08	.016	.026	462	30
λ = .85												
Single-factor model	0	241.9	31.6	9	.67	.04	.45	.07	.360	.025	0	12
Two-factor model	0	4.3	3.0	4	1.00	.00	1.00	0.02	.024	.032	488	0
					r = .65							
λ = .55												
Single-factor model	162	20.7	8.6	9	.91	.06	.85	.11	.074	.033	53	0
Two-factor model	1	3.1	2.1	4	1.00	.01	1.03	0.07	.013	.022	342	105
λ = .85												
Single-factor model	175	177.0	28.6	9	.78	.04	.63	.07	.305	.026	0	8
Two-factor model	1	3.9	2.9	4	1.00	.00	1.00	.01	.020	.030	492	0
					r = .80							
λ = .55												
Single-factor model	402	13.6	6.4	9	.96	.04	.95	.07	.043	.033	141	0
Two-factor model	0	2.9	1.9	4	1.00	.01	1.03	0.05	.011	.020	137	222
λ = .85												
Single-factor model	500	92.1	21.9	9	.89	.03	.83	.05	.213	.029	0	0
Two-factor model	0	4.2	3.11	4	1.00	.00	1.00	0.02	.022	.032	500	0

Note. Results are based on 500 replications for each condition. Columns of chi-square, comparative fit index (CFI), Tucker–Lewis index (TLI), and root-mean-square error of approximation (RMSEA) represent the means and standard deviations of the simulated values. Columns of Guttman–Kaiser criterion (G–K) decision and Akaike information criterion (AIC) decision represent the number of supported models based on these criteria. No. improper = number of improper solutions.

factor loadings (i.e., low internal consistency) often reflect the fact that participants respond to the items less coherently because the constructs assessed by the items are ambiguously defined or operationalized (Cronbach & Gleser, 1965). Thus, definitional or operational ambiguity makes it difficult to distinguish one construct from another, similar construct. Importantly, this is not the case for the AGQ-R; the AGQ-R was based on a very precise definition and operationalization of achievement goals (Elliot & Murayama, 2008), resulting in high internal consistency and high factor loadings (ranging from .82 to .93 in Study 1a). Our simulation results suggest that it is this property of the AGQ-R that makes it possible to distinguish between the highly correlated performance-approach and performance-avoidance goals.

Study 2

Study 2 was designed to test the separability of performance-approach and performance-avoidance goals in terms of change. Specifically, we assessed the two goals at two time-points and conducted a series of CFAs on the change scores.

Method

Participants and procedure. Two samples were obtained: 301 U.S. university students (103 men and 198 women; 200 Caucasian, 15 African American, 63 Asian American, 11 Hispanic, and 12 others; mean age = 19.27 years) taking a psychology class and 165 Japanese junior high school students (75 boys and 90

girls; mean age = 12.07 years) taking a mathematics class. For the U.S. university sample, participants completed a questionnaire assessing their current achievement goals for each of two exams (5 weeks apart); participants completed each questionnaire 1 week before the exam. For the Japanese junior high sample, participants completed a questionnaire assessing their current achievement goals for their mathematics class at two time-points during a semester (7 weeks apart).

Performance-approach goal and performance-avoidance goal scales. The goals were assessed with the same measures used in Study 1a (the AGQ-R for the U.S. university sample and a translated version of the AGQ-R for the Japanese junior high sample).

Results and Discussion

Preliminary analysis. Before investigating separation per se, we conducted a preliminary analysis examining the longitudinal invariance of the factor structure for each sample (see Meredith & Horn, 2001). In this analysis, CFA was conducted with a hypothesized model that assumed the same factor structure across time-points. Specifically, within a time-point, the items for each goal were assumed to load on their respective latent variables. Between time-points, all the latent variables were assumed to be correlated. Moreover, the factor loadings on the same indicators and the factor correlation between the performance-approach and performance-avoidance goals were constrained to be equal across time-points. Correlated errors between the same indicators across time-points

were first assumed and then were omitted from the model if the magnitude of the correlation was negligible (less than .10).

The model showed a good fit to the data for the U.S. university sample, $\chi^2(50) = 83.05$, $p < .01$, CFI = .99, TLI = .99, RMSEA = .047, and for the Japanese junior high sample, $\chi^2(51) = 102.32$, $p < .01$, CFI = .96, TLI = .94, RMSEA = .078. All factor loadings were quite high (ranging from .77 to .94). These results extend those of Study 1a by showing the separation of cross-sectional performance-approach and performance-avoidance goals across different time-points.

Given the presence of longitudinal measurement equivalence, we proceeded to conduct a latent change analysis (McArdle & Nesselroade, 1994). This is a submodel of the latent growth curve model (McArdle & Anderson, 1990), and using this model enables one to test whether change in a construct has sufficient between-person variability to conduct a full analysis. The model was essentially the same as the previous measurement invariance model, except we assumed two (higher order) latent variables representing intercepts and changes between time-points for each construct. Accordingly, for both samples, the variability (i.e., variances) of true change scores was examined. Results showed that all the change tested in the analysis had significant variability between participants for both performance-approach goals and performance-avoidance goals (ps < .01); this indicates that the necessary condition for conducting analyses for change scores was satisfied.

Change CFA. To conduct the analysis, we first calculated a change score for each item by computing difference scores between the two time-points. Next, we conducted a series of CFAs with the change scores to examine the separability of performance-approach and performance-avoidance goals based on the covariation of the change scores. A single-factor model, in which all six indicator variables (i.e., change scores for each item) were explained by a single latent factor, was compared with a two-factor model in which two latent variables, representing performance-approach and performance-avoidance goals, loaded on their respective indicator variables. The results strongly supported the two-factor model (see Table 6), with good fits for the U.S. university sample, $\chi^2(8) = 14.21$, $p = .08$, CFI = .99, TLI = .98, RMSEA = .052, and for the Japanese junior high sample, $\chi^2(8) = 16.31$, $p < .05$, CFI = .97, TLI = .94, RMSEA = .080. All the factor loadings were quite substantive, ranging from .58 to .78. In contrast, the single-factor models showed a poor fit to the data for the U.S. university sample, $\chi^2(9) = 65.90$, $p < .01$, CFI = .90, TLI = .84, RMSEA = .147, and for the Japanese junior high

sample, $\chi^2(9) = 44.15$, $p < .01$, CFI = .87, TLI = .78, RMSEA = .155. Moreover, the AIC favored the two-factor model for both samples. These results indicate that performance-approach and performance-avoidance goals are separate constructs even in terms of their change.

Multigroup CFA. We performed a series of multigroup CFAs to examine the equivalence of the factor structure based on change scores across samples. Again, a configural invariance model, a metric invariance model, and a (factor) variance–covariance invariance model were sequentially tested.

The results supported not only the configural and metric invariance models but also the most constrained variance–covariance invariance model (see Table 7), with all the multigroup CFAs showing a good absolute fit: $\chi^2(31) = 38.78$, $p < .05$, CFI = .98, TLI = .97, RMSEA = .038. The results also showed good change in fit (ΔCFI = $-.005$, ΔTLI = $-.006$). The disattenuated factor correlation was .71. These results indicate that the two-factor structure in achievement goal change is invariant across samples in terms of equivalent factor loadings and the factor correlation.

Study 3

The purpose of Study 3 was to examine the separation of performance-approach and performance-avoidance goals after reducing response bias. By response bias we mean the tendency to distort responses in a particular direction to all the items, due, at least in part, to semantic overlap among the items (M. W.-L. Cheung & Chan, 2002). Respondents who are not carefully attending to the items may answer similarly based on a response set, which would introduce systematic correlated errors of measurement and produce an inflated correlation between the goals.

One approach to reducing response bias that has been shown to be effective is to use ipsative measurement (M. W.-L. Cheung, 2006; Gurwitz, 1987). An ipsative measure is one in which the sum of the scores over the items for each individual equals a constant. A constant sum of item scores makes it impossible for the item scores to be uniformly high or low within a given individual. Accordingly, the ipsative scores for each individual cannot be distorted in a particular direction across items, resulting in a reduction of response bias. In this study, we examined the factor structure of performance-approach and performance-avoidance goals using a paired-comparison method that afforded ipsative measurement. With the paired-comparison method, respondents are presented with pairs of items and instructed to select the more preferred alternative from each pair, and a constant point is added

Table 6

Study 2: Model Testing in Confirmatory Factor Analysis Based on Change Analysis

Sample	χ^2	df	CFI	TLI	RMSEA	AIC
U.S. university						
Single-factor model	65.90	9	.90	.84	.147	4288.43
Two-factor model	14.21	8	.99	.98	.051	4238.74
Japanese junior high						
Single-factor model	44.15	9	.87	.78	.155	2671.68
Two-factor model	16.31	8	.97	.94	.080	2645.84

Note. CFI = comparative fit index; TLI = Tucker–Lewis index; RMSEA = root-mean-square error of approximation; AIC = Akaike information criterion.

Table 7
Study 2: Model Testing in Multigroup Confirmatory Factor Analysis Based on Change Analysis

Model	χ^2	df	CFI	TLI	RMSEA	$\Delta\chi^2$	ΔCFI	ΔTLI
Configural invariance	30.38	16	.98	.96	.044			
Metric invariance	31.41	20	.99	.97	.035	1.03	.003	.016
Variance–covariance invariance	38.78	23	.98	.97	.038	7.37	−.005	−.006

Note. CFI = comparative fit index; TLI = Tucker–Lewis index; RMSEA = root-mean-square error of approximation; $\Delta\chi^2$ = change in chi-square; ΔCFI = change in comparative fit index; ΔTLI = change in Tucker–Lewis index.

to the selected items. The number of comparisons participants make is the same across participants, so the sum of the scores over the items for each individual is also the same, resulting in ipsative measurement. Given that participants are not allowed to agree with both alternatives from a pair of items, this method helps reduce response bias (i.e., the tendency to respond in a particular direction to all items). From a different standpoint, this method requires participants to carefully consider and select items in each comparison and, accordingly, may afford better discrimination of the performance-approach and performance-avoidance goal items, if, in fact, they may be discriminated (see Van Yperen, 2006). If participants cannot distinguish between the items, the item scores are ranked similarly within each person and should be clustered together in factor analysis.

Method

Participants and procedure.   Ninety-seven Japanese university students (59 men and 38 women; mean age = 18.54 years) taking a statistics class participated in the study. Participants completed a questionnaire assessing their achievement goals for a class.

Performance-approach goal and performance-avoidance goal measures.   The goal questionnaire was composed of the pairwise comparison of six items (three representing performance-approach goals and three representing performance-avoidance goals). Each of the six items was compared with each of the other five items one at a time, constituting 15 pairwise comparisons in total. From each pair, participants were instructed to select the goal that they were most engaged in. To avoid carry-over effects due to presentation order, we created four versions of the questionnaire that randomized the presentation order of the pairs, as well as the order of the items within each pair, and participants were randomly assigned to one of the four item orders.

The six goal items were based on the AGQ-R items, but two changes were made. First, in the AGQ-R, all the items have a

goal-based prefix (e.g., "My goal is to . . ."), but in the context of paired comparison, it is redundant to repeat this prefix for all items. Accordingly, this prefix was removed from all items. Second, we rephrased the performance-avoidance goal items so that the wording was the same as the corresponding performance-approach goal item, excepting the valence component. For example, for the performance-approach goal item "to do well compared to other students on this exam," we rephrased the corresponding performance-avoidance goal item to be "to avoid doing poorly compared to other students on this exam." This approach to item construction accentuated similarity of wording and thus afforded an extremely conservative test of separation.

Results and Discussion

Item scores were computed by counting the number of times each item was selected. The possible range of item scores was 0–5, because each item was included in five comparisons. The sample correlation matrix of these six items is reported in Table 8. It should be noted that one cannot take the correlation coefficients displayed in Table 8 at face value, because the correlation matrix obtained from ipsative data is, in principle, negatively biased (M. W.-L. Cheung & Chan, 2002; Dunlap & Cornwell, 1994). However, it is still clear from the correlation matrix that participants distinguished the items representing performance-approach goals from those representing performance-avoidance goals, as the pattern of correlations is more clustered within the item sets assessing the same goal.

Although the observed correlation matrix suggests separation, CFA is a stronger test of separation. However, it is widely known that there is a statistical difficulty in conducting factor analysis with ipsative data (Dunlap & Cornwell, 1994). Due to the constant-sum constraint, the sample covariance (or correlation) matrix is always singular as a function of the linear dependence of the item scores. As a result, standard CFA is impossible. To address this problem, we applied an ipsative factor-analytic tech-

Table 8
Study 3: Sample Correlation Matrix for Ipsative Data

Item	1	2	3	4	5	6
1. Performance-approach goal Item 1	—					
2. Performance-approach goal Item 2	.17	—				
3. Performance-approach goal Item 3	.17	.46	—			
4. Performance-avoidance goal Item 1	−.41	−.46	−.68	—		
5. Performance-avoidance goal Item 2	−.51	−.52	−.60	.40	—	
6. Performance-avoidance goal Item 3	−.37	−.53	−.34	.04	.19	—

nique proposed by Chan and Bentler (1993). In this technique, a covariance matrix is computed after deleting the last variable of the data set to avoid singularity of the matrix, and parameter estimates of a hypothesized factor model are calculated based on the results obtained from this reduced covariance matrix (Chan & Bentler, 1993). This specific parameterization makes it possible to estimate the factor loadings and factor correlations assumed in standard CFA.

In addition, because the covariance structure of ipsative factor analysis is complex, the model is susceptible to nonconvergence, and it is sometimes necessary to constrain the model parameters to overcome this problem (Toyoda, 2000; see also Chan & Bentler, 1993). Accordingly, we first imposed equality constraints on the factor loadings and error variances of the items that shared the matched wordings and then freed one of the constraints to address the nonconvergence issue. This model converged normally, and the results revealed a good fit of the model to the data, $\chi^2(7) = 11.36$, $p = .12$, CFI = .98, TLI = .97, RMSEA = .080. The factor loadings are quite substantive, ranging from .51 to .93. Importantly, the estimated (disattenuated) factor correlation between performance-approach and performance-avoidance goals was .31, which is much smaller than the values observed in Study 1a. This relatively smaller correlation (after correcting for measurement error) suggests that the observed high correlation between the goals in previous research can, to some extent, be accounted for by response bias.

Study 4

Study 4 investigated the within-person separation of performance-approach and performance-avoidance goals. Specifically, we had participants rate their goals in five situations; this allowed us to conduct factor analyses based on within-person covariation.

Method

Participants and procedure.   Seventy-three U.S. university students (15 men and 58 women; 42 Caucasian, 10 African American, 12 Asian American, 3 Hispanic, and 6 others; mean age = 19.81 years) participated in the study. Participants completed a questionnaire packet assessing their performance approach and performance-avoidance goals in five competence-relevant situations.

Situations and performance-approach goal and performance-avoidance goal scales.   The five situations that were selected for the achievement goal assessment were as follows: a class, a sport or exercise event, work at a job, a hobby or extracurricular activity, and a social situation involving success or failure. Participants were instructed to write down their most recent experience related to each situation and to rate, on a 5-point Likert-type scale, the performance-approach and performance-avoidance goals that they had adopted in that situation. The AGQ-R was used to assess the goals, but slight changes were made to the items so that the same wording could be used in all five situations. Accordingly, the three performance-approach and three performance-avoidance goal items were strictly parallel across the five situations.

Results and Discussion

Pooling scores of individuals in each situation without considering the multilevel nature of the data (situations nested within persons) would produce biased parameter estimates (Nezlek, 2001). The sample covariance obtained from such pooled data would confound within-person and between-person covariance (Mehta & Neale, 2005) and would not reflect within-person variation per se. In fact, the intraclass correlations of the items in our data ranged from .21 to .42, indicating substantive bias resulting from pooling the data (Raudenbush & Bryk, 2002). Accordingly, we used multilevel structural equation modeling (Muthén, 1994), because it allowed us to directly model the within-person covariance structure of the data.

In the multilevel structural equation modeling analysis, we created a model in which two latent variables representing performance-approach and performance-avoidance goals loaded on their respective indicator variables at the within-person level. This two-factor model represented the separation of performance-approach and performance-avoidance goals within an individual. ML estimation of the two-factor model showed a good fit to the data, $\chi^2(8) = 9.97$, $p = .27$, CFI = 1.00, TLI = 1.00, RMSEA = .026, with high factor loadings ranging from .86 to .93. The disattenuated factor correlation was .78. For the purpose of comparison, we also created a single-factor model in which only one latent variable explained all the indicator variables at the within-person level. This model showed a poor fit to the data, $\chi^2(9) = 241.99$, $p < .01$, CFI = .89, TLI = .64, RMSEA = .266. The AIC also favored the two-factor model: AIC = 5175.38 for the two-factor model, AIC = 5405.40 for the single-factor model. These results clearly indicate that performance-approach and performance-avoidance goals are separable based on within-person analysis.

Study 5

In Study 5, we examined the genetic and environmental structures of performance-approach and performance-avoidance goals. By means of twin data, four general sources of variance and covariance can be estimated (Neale & Cardon, 1992): additive genetic effects (A), nonadditive genetic effects (D), common environmental effects (C), and nonshared environmental effects (E). The first two effects represent genetic influences. Additive genetic effects comprise the total summative influence of multiple genes, each of which has a small main effect. Nonadditive genetic effects refer to the total summative influence of intralocus or interlocus genetic interactions; both represent an interaction in the sense that the expression of one genetic variant depends on the presence of another genetic variant. Common environmental effects represent influences that are shared by twins within a family. Nonshared environmental effects refer to the component of environmental influence that is not shared by twins within a family, including random error variance. We fit multivariate as well as univariate genetic models to the data in order to examine the differential contribution of these effects to performance-approach and performance-avoidance goals.

Method

Participants and procedure.   Participants were 289 monozygotic twin pairs (108 male pairs, 162 female pairs, and 19 unspec-

ified) and 276 dizygotic twin pairs (70 male pairs, 75 female pairs, 118 opposite-sex pairs, and 13 unspecified) from Japan, with ages ranging from 13 to 18 years old ($M = 15.33$). Zygosity was diagnosed with a well-established questionnaire in Japan (Ooki, Yamada, Asaka, & Hayakawa, 1990) that assesses the frequency of one twin being mistaken for another by different relatives in childhood. The sample was recruited by postal mail from a population-based twin residential list of Tokyo and neighboring cities. Participants completed a questionnaire assessing their current achievement goals for their mathematics class.

Performance-approach goal and performance-avoidance goal scales. The goals were assessed with the same measure used in Study 1a and Study 2 with the Japanese junior high samples (the translated AGQ-R). Participants rated their goals on a 6-point Likert scale.

Results and Discussion

Univariate analyses. Item scores were averaged to form performance-approach and performance-avoidance goal indexes, and a series of univariate genetic models were fitted to twin pair covariance matrices with ML estimation. To examine the relative importance of A, D, C, and E, we fitted the ACE, ADE, AE, CE, and E models for each phenotype (see Table 9). Models including nonadditive genetic effects (D) without additive genetic effects (A) are biologically implausible (Neale & Cardon, 1992); therefore we did not test such models. Following convention in behavioral genetics research, we compared models using the AIC. The best fitting model for performance-approach goals was the ADE model, $\chi^2(6) = 0.73$, $p = .99$, in which a large proportion of the phenotypic variance was explained by nonadditive genetic effects (45%) and nonshared environmental effects (53%), and a small portion was explained by additive genetic effects (2%). On the other hand, the best fitting model for performance-avoidance goals was the AE model, $\chi^2(7) = 4.58$, $p = .71$, in which the phenotypic variance was explained by additive genetic effects (37%) and nonshared environmental effects (63%).

In a supplementary analysis, we also conducted a common pathway model (for details, see Neale & Cardon, 1992) with the

items of each subscale in order to separate measurement error from the observed scores. In this model, the univariate analysis is applied to the latent factor of the observed variables, thus allowing elimination of measurement error. For performance-approach goals, the analysis produced the estimates of 51% for nonadditive genetic effects, 49% for nonshared environmental effects, and 0% for additive genetic effects. For performance-avoidance goals, the analysis produced the estimates of 42% and 58% for additive genetic and nonshared environmental effects, respectively.

Multivariate analyses. The preceding univariate analyses suggest that between-person variation in performance-approach and performance-avoidance goals is influenced by both genes and nonshared environment. However, the univariate results do not tell us anything about whether the relation between performance-approach and performance-avoidance goals is influenced by different genetic and nonshared environmental effects. To address this question, we conducted multivariate genetic analyses. Multivariate genetic analysis is a technique that partitions the covariation between multiple measures into genetic and environmental components, thus allowing examination of the factor structure of these effects.

We used an independent pathway model (McArdle & Goldsmith, 1990; Neale & Cardon, 1992) in the analyses. This class of model specifies one or more additive genetic, nonadditive genetic, common environmental, and nonshared environmental factors behind the observed variables, which makes it possible to explore the factor structure of each (additive genetic, nonadditive genetic, common environmental, or nonshared environmental effect). In our analyses, we compared eight ($2 \times 2 \times 2$) models in which a single or two common factors of additive genetic, nonadditive genetic, and nonshared environmental effects were specified (Models 1–8; see Table 10). Common environmental factors were not considered, because we did not find any common environmental effects in the univariate analysis. When more than one common factor was specified for each effect, we constrained one of the factor loadings to be zero to identify the model. This is equivalent to estimating an unrotated factor pattern in EFA.

Table 9

Study 5: Univariate Variance Estimates of Additive Genetic, Nonadditive Genetic, Common Environmental, and Nonshared Environmental Contributions to Performance-Approach and Performance-Avoidance Goals

Model	χ^2	df	AIC	A	D	C	E
Performance-approach goal							
ACE	3.72	6	5834.05	.45		.00	.55
ADE	**0.73**	**6**	**5831.07**	**.02**	**.45**		**.53**
AE	3.72	7	5832.05	.45			.55
CE	21.41	7	5849.80			.31	.70
E	70.12	8	5896.45				1.00
Performance-avoidance goal							
ACE	4.48	6	5576.27	.33		.04	.63
ADE	4.58	6	5576.38	.37	.00		.63
AE	**4.58**	**7**	**5574.38**	**.37**			**.63**
CE	8.67	7	5578.47			.29	.71
E	52.08	8	5619.87				1.00

Note. The best fitting models are in bold. AIC = Akaike information criterion; A = additive genetic effects; D = nonadditive genetic effects; C = common environmental effects; E = nonshared environmental effects.

Table 10

Study 5: Comparison of Eight Independent Pathway Models Specifying Different Numbers of Common Factors

Model	Number of common factors			χ^2	df	AIC
	A	D	E			
1	1	1	1	383.77	138	18873.28
2	1	1	2	242.84	133	18742.36
3	1	2	1	354.57	133	18854.08
4	2	1	1	356.57	133	18856.09
5	1	2	2	206.49	128	18716.01
6	**2**	**1**	**2**	**205.54**	**128**	**18715.06**
7	2	2	1	353.56	128	18863.09
8	2	2	2	202.53	123	18722.04

Note. The best fitting model is in bold. A = additive genetic effects; D = nonadditive genetic effects; E = nonshared environmental effects; AIC = Akaike information criterion.

The model comparison results in Table 10 indicate that the best fitting model was Model 6, in which two additive genetic factors, a single nonadditive genetic factor, and two nonshared environmental factors were specified. Factor patterns are presented in Table 11. For the additive genetic and nonshared environmental factors, we rotated the obtained factor patterns using oblique Procrustes rotation to test the hypothesized two-factor structure (i.e., the items for each goal were targeted to load only on their respective latent factors; see J. R. Hurley & Cattell, 1962). We performed the factor rotation using the SAS FACTOR procedure. The obtained factor pattern supported a simple structure, indicating the separation of performance-approach and performance-avoidance goals for both additive genetic and nonshared environmental effects. The factor correlations of additive genetic factors and nonshared environmental factors were .39 and .49, respectively. In addition, consistent with the univariate analysis, the nonadditive genetic factor had larger factor loadings on performance-approach goal items, providing additional evidence for separation in terms of the specificity of nonadditive genetic effects. In sum, these results provide strong support for the separation of performance-approach and performance-avoidance goals based on genetic and nonshared environmental effects.

General Discussion

The present research comprised five studies using diverse methods to examine the separability of performance-approach and performance-avoidance achievement goals. The results supported construct separation from multiple perspectives. Study 1 showed that EFA, as well as CFA, supports the separation of two goals across different age groups (university students and junior high school students) and countries (United States and Japan). Study 2 showed separation in performance-approach and performance-avoidance goal change. Study 3 showed separation and a reduced correlation between performance-approach and performance-avoidance goals after response bias was minimized through use of ipsative measurement. Study 4 indicated that within-person analysis yields evidence for performance-approach and performance-avoidance goal separation. Study 5 indicated that performance-approach and performance-avoidance goals are separable in terms of their genetic and environmental origins.

Our research provided evidence supporting the separation of performance-approach and performance-avoidance goals across different age groups (i.e., junior high school and undergraduate students) and countries (i.e., United States and Japan) and documented factorial invariance among them. These findings fit nicely with theoretical models emphasizing the independence of approach and avoidance motivation at the level of biological structure and function (Cacioppo & Gardner, 1999; Elliot & Thrash, 2002; Gray & McNaughton, 1996). We do not dispute that success and failure may have different connotations among different age groups or within different countries (Li, 2003; Maehr & Nicholls, 1980; Nicholls, 1989), nor that the correlates of performance-

Table 11

Study 5: Factor Loadings and Factor Correlations in Multivariate Behavioral Genetic Analysis

Effect type	Item 1	Item 2	Item 3	Item 4	Item 5	Item 6	Factor correlation
Additive genetic							
Factor 1	**0.846**	**0.513**	**0.482**	−0.038	0.363	−0.109	.39
Factor 2	−0.040	0.023	0.220	**0.673**	**0.488**	**0.786**	
Nonadditive genetic							
Factor 1	**0.438**	**0.862**	**0.651**	0.281	0.152	0.324	
Nonshared environmental							
Factor 1	**0.971**	**0.907**	**0.830**	0.076	0.293	0.130	.49
Factor 2	−0.120	0.013	0.132	**0.848**	**0.597**	**0.745**	

Note. Loadings greater than .40 in absolute magnitude are in bold. Items 1–3 assess performance-approach goals, and Items 4–6 assess performance-avoidance goals.

approach and performance-avoidance goals may differ across ages or countries (see Bong, 2009; Elliot, Chirkov, Kim, & Sheldon, 2001; Tanaka & Yamauchi, 2001). Rather, our contention is that approaching success and avoiding failure may represent widely understood concepts that people of different ages and in different countries can differentiate, even if the concepts have unique connotations across age and/or country. It should be noted that our results were based on samples from two specific countries (United States and Japan) and two specific age groups (junior high school and undergraduate students). We believe that these samples are heterogeneous enough to add substantial information regarding the generalizability of the separation findings, but we also acknowledge that further research is needed before a strong statement can be made that the two goals are separable across culture or developmental trajectory. In addition, because we did not examine age or country differences in our response bias, within-person, and behavioral genetics studies (in Studies 3–5), the generalizability of the findings from these investigations must be considered an open question.

Our research obtained evidence of separation using EFA, as well as CFA. One important insight from our EFA results is that reliance on the conventional Guttman–Kaiser criterion to determine factor selection can be misleading in evaluating the number of factors in a data set. Despite its popularity, the weaknesses of the Guttman–Kaiser criterion have been pointed out in several articles, and researchers have called for the need to replace the Guttman–Kaiser criterion with an alternative approach to factor selection (Fabrigar et al., 1999). Most notably, previous studies have indicated that the Guttman–Kaiser criterion underestimates the number of factors when factors are correlated, which is exactly the case herein. Both our empirical (Study 1a) and simulation (Study 1b) studies provide clear evidence of the limitations of the Guttman–Kaiser criterion and highlight the importance of using statistical fit indices to determine the proper number of factors.

In most of the studies that we presented, the factor loadings from the factor analyses were quite strong. These strong factor loadings reflected precise measurement (i.e., high measurement model quality; Gagné & Hancock, 2006) of the focal constructs, and it is likely these well-defined items that made it possible to empirically differentiate the highly correlated performance-approach and performance-avoidance goals. In fact, our simulation findings in Study 1b showed high internal consistency (as a function of high factor loadings) to be a necessary condition for a two-factor model to be accurately discriminated from a single-factor model when two constructs are highly correlated. We would not argue against broad bandwidth scales in general, as this approach has borne much fruit in some areas of psychology (especially personality psychology; Hogan & Roberts, 1996). Rather, with Loevinger (1957), we simply argue for careful definition and operationalization of constructs in all measurement contexts and think that future scale development studies on achievement goals would do well to bear this point in mind.

A number of studies over the past few years have examined the degree to which achievement goals change over time (E. M. Anderman & Midgley, 1997; L. H. Anderman & Anderman, 1999; Bong, 2005; Seifert, 1996; Senko & Harackiewicz, 2005), and researchers have recently begun to focus on within-person variation in achievement goals (Fryer & Elliot, 2007). It seems that the emerging research on change and within-person covariation has

proceeded without attending to the issue of factorial separation. We suspect that this oversight is based on the incorrect assumption (see Hamaker et al., 2005; Molenaar & Campbell, 2009) that factorial separation with standard between-person covariation translates directly to factorial separation with other types of covariation. The present research is the first to empirically document a parallel factorial structure for performance-approach and performance-avoidance goals across different types of covariation, thus laying the foundation for future work with these different methodological approaches. We should note that our studies focused on a particular type of change (i.e., change between two time-points) and a particular type of within-person assessment (i.e., variation between different achievement situations), and that other types of change and within-person assessment are also applicable to the question at hand. For example, by collecting data at more than two time-points, future work could examine change in terms of slope (see Shim et al., 2008) or acceleration (i.e., change in rate of change; see Chow, Ram, Boker, Fujita, & Clore, 2005; Deboeck, Montpetit, Bergeman, & Boker, 2009). In addition, by using diary or experience sampling methodologies, future work could investigate within-person variation that takes into account the temporal structure of construct variation.

Our research is also the first to conduct a behavioral genetic analysis of achievement goals and, indeed, is one of the first to apply behavioral genetic methods to the topic of motivation more generally (see B. Spinath, Spinath, Harlaar, & Plomin, 2006; F. M. Spinath, Spinath, & Plomin, 2008). We performed univariate as well as multivariate analyses and found that additive genetic, nonadditive genetic, and nonshared environmental factors had a differential influence on both the individual goals and their covariation. Shared environmental factors did not influence either the individual goals or their covariation. Additional research is needed to determine the specific genes and unique environmental factors that underlie achievement goal adoption and to explore why shared environment is of such little consequence (as is the case, surprisingly, for many personality variables; for a review, see Johnson, Vernon, & Feiler, 2008). The finding that performance-approach and performance-avoidance goals have a genetic basis is consistent with theorizing that grounds achievement goals in temperaments and other heritable dispositions (Bipp, Steinmayr, & Spinath, 2008; Elliot & Thrash, 2010); that shared environment has little impact on these goals is more difficult to square with current theorizing.

Hulleman, Schrager, Bodmann, and Harackiewicz (2010) recently documented that the focus of the items that are used to assess achievement goals differ substantially from measure to measure and that these different operationalizations impact relations with other variables (see also Elliot & Thrash, 2001; Urdan, 2004b). In the current research, we used achievement goal items focused specifically on normative comparison (Elliot & Murayama, 2008). That is, the measures we used did not include related, but conceptually distinct, constructs such as underlying achievement values and motives, and did not emphasize the external or social nature of competence evaluation. We believe that our exclusive focus on normative items afforded a particularly strong test of separation, because the subscales of performance-approach and performance-avoidance goals have quite similar structure and content. However, the current research is mute on whether measures based on other conceptualizations evidence sep-

aration; future work is needed to examine separation using different types of achievement goal measures. On a related note, the extant scales also differ in terms of the number of scale points (e.g., a 5-point scale or a 7-point scale) provided to respondents. In addition, the use of an odd number of response options may introduce ambiguity in the meaning of the scale midpoint (i.e., *neither agree nor disagree*), and it is possible that these factors also influence the separation of performance-approach and performance-avoidance goals. Previous research suggests that such factors have little impact on the reliability and validity of measurement (e.g., Armstrong, 1987; Matell & Jacoby, 1971), but we are not aware of any empirical work that has examined this measurement issue with regard to factorial separation, and the present research is mute on this matter. Future research is needed in this area.

Although we provided several types of evidence for factorial separation in the present work, the fact remains that the correlation between performance-approach and performance-avoidance goals is moderate to high (see Table 1) across different samples and methodologies. As we have indicated, the two goals share both an investment in competence (i.e., competence valuation) and a core aspect of competence (i.e., a normative standard for competence evaluation), which undoubtedly accounts for a substantial portion of this correlation. Study 3 of the present research also implicates response bias. Items assessing the two performance-based goal constructs use similar wording (increasingly so in recent years), and the influence of this semantic overlap is undoubtedly exacerbated to the extent that items representing the two constructs are clustered together and/or participants have minimal incentive to read and respond to each item carefully (P. M. Podsakoff et al., 2003).

Regardless of the reasons for the relatively high correlation among the two goals, it is important to consider possible implications of this intergoal relation. From a statistical point of view, a high correlation among variables can introduce unstable parameter estimates in regression analysis due to multicollinearity. This may lead some to question the use of regression analysis in examining the predictive utility of performance-approach and performance-based goals. However, regression analysis is actually quite valuable in this context, in that it reveals the effect of each goal after partialing out the shared variance between the goals, thus allowing the detection of goal effects uncontaminated by response bias and other artifacts. The critical point in this consideration is the fact that multicollinearity does not bias parameter estimates (Goldberger, 1991); it only inflates the standard error of the parameter estimates. Therefore, as long as relatively large sample sizes are used or findings can be replicated across different samples, the use of regression analysis is justified, even in cases in which the predictor variables, such as performance-approach and performance-avoidance goals, are highly correlated.

From a practical point of view, the sizable correlation between the two goals is one of many reasons that we believe it is best for teachers not to emphasize performance-approach goals in the classroom. Even if a teacher highlights the value of performance-approach goal pursuit in the classroom, many students would undoubtedly adopt performance-avoidance goals as well as performance-approach goals (see Brophy, 2005; Roeser, 2004; Urdan & Mestas, 2006), with inimical consequences. Related to this pragmatic issue is the overlooked empirical question of what

person- and/or situation-based factors moderate the high correlation between performance-approach and performance-avoidance goals. We suspect that individuals' perceptions of competence may be an important moderator in this regard. Specifically, when perceived competence is high, individuals may be able to strive for normative success relatively unencumbered by concerns about failure (leading to a relatively modest positive correlation), but when perceived competence is low, approaching normative success and concerns about failure may tend to be commingled (leading to a relatively strong positive correlation). We are currently exploring this possibility in a series of studies, and early returns look promising.

A limitation of our research is that we examined the separation question by focusing on issues pertaining to factor analysis without examining another aspect of construct validity, that of divergent validity (i.e., whether two constructs are similarly or differentially related to another variable; Campbell & Fiske, 1959). Focusing on divergent validity may seem unnecessary given that many previous studies have documented that performance-approach and performance-avoidance goals are linked to different antecedents and outcomes (for reviews, see Darnon, Butera, Mugny, Quiamzade, & Hulleman, 2009; Elliot & Moller, 2003; Hulleman et al., 2010; Kaplan & Maehr, 2007; Payne, Youngcourt, & Beaubien, 2007; Rawsthorne & Elliot, 1999; Ryan, Ryan, Arbuthnot, & Samuels, 2007; Wolters, 2004). However, these findings are based on standard between-person variation, and research examining divergent validity in the context of change in achievement goals, within-person analysis of achievement goals, or genetic–environmental correlates of achievement goals would be welcomed. It should be noted that the documentation of divergent validity may not, in and of itself, be unambiguous evidence for construct separation. As classical theories of factor analysis indicate, an observed score of an item represents a composite of the focal construct and idiosyncratic features of the item (e.g., an affective component attached to the item). Accordingly, when two variables are differentially linked to another variable, it remains unclear whether the construct per se or an idiosyncratic feature of an item is responsible for the differential relation. Evidence for factorial validity and divergent validity should be considered in concert; neither is inherently superior to the other.

In making judgments about construct separation, researchers emphasizing parsimony run the risk of collapsing together constructs that should be separated, whereas those emphasizing explanatory power run the risk of positing two constructs when one would suffice. The former tendency undoubtedly leads to "jingle fallacies" (whereby two distinct constructs are mistakenly given the same label; Thorndike, 1904) and the latter to "jangle fallacies" (whereby different labels are mistakenly given for the same construct; Kelley, 1927). Both of these fallacies greatly impede scientific progress (Block, 1995; Marsh, 1994). Factor-analytic techniques are of great benefit when striving to evade these dual and dangerous fallacies, but the use of factor-analytic techniques has been unnecessarily narrow and restricted. This is the case not only for the constructs investigated herein—performance-approach and performance-avoidance goals—but for many other constructs in the psychological literature (e.g., self-efficacy and academic self-concept, Lent, Brown, & Gore, 1997; Marsh, Dowson, Pietsch, & Walker, 2004; Pietsch, Walker, & Chapman, 2003; positive affect and the absence of negative affect, Larsen, McGraw, & Cacioppo,

2001; Russell & Carroll, 1999; Watson & Tellegen, 1999; subjective well-being and self-esteem, Diener & Diener, 1995; Huebner, Gilman, & Laughlin, 1999; Lucas, Diener, & Suh, 1996; competence and liking within global self-esteem, Mar, DeYoung, Higgins, & Peterson, 2006; Tafarodi & Swann, 1995; and pessimism and neuroticism, Scheier, Carver, & Bridges, 1994; Smith, Pope, Rhodewalt, & Poulton, 1989). Accordingly, we hope that the present research not only provides a clear answer on the question of the separability of performance-approach and performance-avoidance goals, but also highlights the need for a broader, more comprehensive approach to the question of construct separation in psychological research more generally.

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Correction to Estrada-Hollenbeck et al. (2010)

In the article "Toward a Model of Social Influence That Explains Minority Student Integration Into the Scientific Community," by Mica Estrada-Hollenbeck, Anna Woodcock, Raul R. Hernandez, and P. Wesley Schultz (*Journal of Educational Psychology*, Advance online publication, November 1, 2010. doi: 10.1037/a0020743), the name of the author Mica Estrada-Hollenbeck should have read Mica Estrada. All versions of this article have been corrected.