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Closing the Excellence Gap: Investigation of an Expanded Talent Search Model for Student Selection Into an Extracurricular STEM Program in Rural Middle Schools

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Abstract

High-potential students from underresourced rural schools face barriers that reduce options for academic advancement, which widens the excellence gap between them and their more affluent, but similar ability peers. The goal of this study was to investigate the effectiveness of an expanded above-level testing model to identify high-potential rural students for an extracurricular math and science enrichment program. Results from our analyses indicated that a more inclusive talent pool differentiated among high achievers to find greater percentages (13%) of talented students compared with most gifted programs (3% to 5%) or Talent Search programs (5%). Overall, students' math and science scores were related to a 75% and 50%, respectively, greater odds in being identified for the extracurricular program. Regardless of program participation, all talent pool students increased their math and science achievement; however, there were some significant gender differences.

Keywords

STEM, rural, excellence gap, identification, middle school, age/developmental stage

Rural schools face unique challenges preparing students for STEM (science, technology, engineering, and mathematics) careers and postsecondary education compared with schools in urban and suburban areas (Schafft & Jackson, 2011). Rural students contend with issues of geographic isolation and insufficient bandwidth to support online access and full adoption of technological advances (Spencer, 2017), limited access to advanced coursework in mathematics and science (National Science Board, 2014), and economic barriers that inhibit future employment and educational opportunities (Lapan, Aoyagi, & Kayson, 2007). Gifted rural students, in particular, represent a culturally unique, underidentified, and underserved population (Howley, Rhodes, & Beall, 2009; Stambaugh & Wood, 2015). In part, this may be due to the technological and economic barriers presenting difficulties for gifted rural students in reaching advanced levels of academic achievement necessary to pursue STEM academic and career success at the highest levels (Kittleson & Morgan, 2012). This lack of access (Planty & Provasnik, 2007), which may lead to reduced engagement in advanced coursework (VanTassel-Baska & Hubbard, 2015, 2016) compared with similar ability students from high-income families (Plucker, Giancola, Healey, Arndt, & Wang, 2015; Plucker & Harris, 2015), reflects the *excellence gap* (Plucker, Burroughs, & Song, 2010). Documented as early as elementary school and persisting through high school (Plucker & Harris, 2015), the excellence gap represents a growing crisis requiring programmatic intervention.

Preparation for and access to advanced coursework and curricula are crucial for establishing effective pathways to successful postsecondary education. Advanced Placement (AP) coursework offers one metric with which to compare schools and the barriers facing high-potential rural students as they pursue math and science at the highest levels (Assouline, Flanary, & Foley-Nicpon, 2015). As reported by Planty and Provasnik (2007), the smaller the enrollment in a school, the lower the likelihood of opportunities for AP coursework. Only 40% of small schools with enrollment less than 500 students offer AP courses, whereas 82% of medium-sized schools with enrollments between 500 and 1,119 students offer AP courses. Similar limitations exist for advanced math courses. For example, students in small, rural schools are less likely than their suburban counterparts to take algebra in Grade 8 (Spielhagen, 2006), or calculus in high school (Cogan, Schmidt, & Wiley, 2001; Kena et al., 2016).

This is relevant because high school enrollment in calculus serves as a strong predictor of bachelor's degree attainment (Adelman, 2006). Yet students can enroll in calculus only if there is the appropriate curriculum sequence that

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includes pre-algebra prior to eighth grade and algebra in eighth grade. In other words, the consequences of being educated in an underresourced school system appear well before high school and can be profound for bright students with college potential in the STEM disciplines. Rural students attend college at percentages (29.3%) that are substantially less than their urban (47.7%) or suburban (42.3%) counterparts (National Center for Education Statistics, 2015).

One approach to addressing these fundamental differences of access to advanced coursework at the high school level, which contributes to an excellence gap, is to offer extracurricular programming at the middle school level. Extracurricular programs have several advantages for high-potential students, especially those from underresourced schools (Plucker & Harris, 2015). The out-of-school hours have the potential to promote positive peer group interactions, socialization, and the development of social as well as academic competencies for high-potential middle school students (Eccles, Barber, Stone, & Hunt, 2003; Olszewski-Kubilius & Lee, 2004). Gira (2007) documented the positive effects of out-of-school activities on the educational success of students at risk due to poverty, including students from rural schools. Lee, Matthews, and Olszewski-Kubilius (2008) posit that extracurricular programming offers opportunities for in-depth study and enriched learning environments. Furthermore, extracurricular programming for at-risk, high-potential, middle school students may serve as an impetus, both psychologically and academically, for seeking advanced coursework in high school (Plucker & Harris, 2015). Developing STEM learning opportunities that are nontraditional and responsive to the local needs of rural students can enable multiple pathways to STEM degrees and careers (National Science Board, 2014).

The goal to improve high-potential rural students' STEM achievement through extracurricular programming must also consider the inclusivity of identification models for such programming. Namely, is the model inclusive enough to generate a broad talent pool of high-achieving students from which a cohort of rural, high-potential students who are ready for talent development opportunities can be identified? There is little research on the effective identification of rural, high-achieving students, and no research on effective domain-specific identification of rural students with talent in math and science (Stambaugh, 2015). Therefore, investigators surmised guidelines for identification and talent development from trends in the research on talent identification, rural education, and gifted education. Three recommendations summarized by Stambaugh (2015) include (a) match identification methods to the program structure and goals, (b) use subtest scores rather than composite scores, and (c) implement team-based decisions grounded in the results from multiple measures.

The talent identification process and out-of-school programming that are the focus of this study incorporated these identification guidelines. The talent search model (Assouline & Lupkowski-Shoplik, 2012; Stanley, 2005), which varies significantly from typical gifted program models in identification format and programming goals (Callahan, Moon, & Oh, 2014), uses above-level tests in specific domains (e.g., math and science) to identify high-achieving students with domain-specific high potential. The purpose of this study was to examine the effectiveness of an expanded talent search model as the identification component of a STEM extracurricular talent development program aimed at developing high-potential rural students in the domains of math and science.

An Extracurricular Talent Development Program for Rural Middle School Students: *STEM Excellence and Leadership*

Concerns about the excellence gap for rural students, coupled with the previously stated propositions, formed the rationale for the development of an advanced math and science extracurricular program, *STEM Excellence and Leadership*, for high-potential students in Grades 6 to 8 in underresourced, rural schools. *STEM Excellence and Leadership* was designed to prepare high-potential, low-income middle school students living in rural areas for advanced STEM coursework in high school.

The first stage of programming involved forming a relatively broad and inclusive talent pool of high-achieving middle school students who could potentially benefit from accelerated extracurricular STEM programming. High-achieving second semester fifth graders (rising sixth graders) formed the talent pool from which the project investigators identified high-potential students for the 3-year program. The *STEM Excellence and Leadership* program was implemented during Grades 6 through 8, with 96 hours of challenging extracurricular math and science content, delivered over a 24-week period throughout each academic year, outside the regular school day. The teachers who implemented the program received professional development in math, science, and gifted education prior to the start of the program. Additional information about the participants appears below.

Identification of High-Potential Students for STEM Excellence and Leadership

Assouline and Lupkowski-Shoplik (2012) detailed the ideological differences between gifted education programs and talent search programs, including differences in philosophy, focus, program setting, and method of identification. Gifted education programs at the elementary level are predominately enrichment-oriented and the focus is on identifying and selecting approximately the top 3% to 5% of students ready for an enrichment curriculum (Callahan et al., 2014). In contrast, the talent search model is a psychometric model in which elementary and middle school students with high-potential (e.g., 95th percentile on a grade-level achievement test; Lupkowski-Shoplik & Swiatek, 1999) in a domain-specific area are discovered through above-level testing; programming then focuses on development of the talent areas revealed through the above-level testing. The identification process for gifted education programs typically relies on general ability measures and/or composite scores on grade-level achievement measures. In contrast, the talent search model typically uses above-level testing in specific content areas, such as math and science.

When considering the general barriers that rural schools and their students face, including the concern about underidentification for gifted programs (Stambaugh, 2015), investigators adapted the talent search model by lowering the guidelines recommended for participation. Whereas the general guideline is the 95th percentile on at least one subtest of a grade-level standardized test (Lupkowski-Shoplik & Swiatek, 1999; Swiatek, 2007), the investigators adjusted the guideline to the 85th percentile on at least one subtest of a grade-level standardized test. Investigators selected the 85th percentile because it represents one standard deviation above the mean on a standardized test and includes students with above average or higher achievement; thus, creating a relatively broad talent pool of high-achieving students recommended for above-level testing.

The content of the above-level test was just more than two grade levels above that of the grade level of students taking the test; therefore, we assumed that the experience would be appropriately challenging but not frustrating despite the fact that the talent pool was more inclusive. This identification method ensured alignment between the identification process and program goals, while objectively forming an inclusive talent pool of high-achieving middle school students. The ultimate goal is for the above-level test results to differentiate among the high-achieving students in the talent pool to discover students with high potential in specific talent domains for participation in STEM extracurricular programming.

The Role of Gender in Talent Identification. The talent search model also offered a robust method for documenting the performance of high-achieving students. In particular, the model has been especially effective at documenting the differences between boys and girls on above-level test performance. A watershed study by Olszewski-Kubilius and Lee (2011) looked at the above-level scores of more than a quarter million participants in a talent search program between 2000 and 2008. In brief, Olszewski-Kubilius and Lee found differences in performance among annual household income levels with students living in households with higher levels of income outperforming those from households with lower income. Equally relevant to the current study, Olszewski-Kubilius and Lee (2011) replicated early findings of gender differences in performance among talent search students (Benbow, 1988; Benbow, Lubinski, Shea, & Eftekhari-Sanjani, 2000). Regardless of age, on above-level tests boys outperformed girls in math and science and girls outperformed boys in reading and language arts. The current study investigated both the performance of high-achieving students from lower income, rural communities and the gender differences in performance.

The Role of Psychosocial Factors in Talent Identification. A seminal study by Csikszentmihalyi, Rathunde, and Whalen (1993) revealed the critical role of psychosocial factors in the academic engagement and success of high-potential adolescents. More recently, Casillas and colleagues (Casillas et al., 2011, Casillas et al., 2012) determined that psychosocial factors measured by a student self-report survey, ACT Engage (ACT, 2016a), explained 33% of the variance in long-term success among students compared with standardized measures of achievement, which explained 27% of the variance. The robustness of psychosocial outcomes for high-potential students has been confirmed in the research on gifted students, writ large (e.g., Kim, 2016; Kroesbergen, van Hooijdonk, Van Viersen, Middel-Lalleman, & Reijnders, 2016); however, psychosocial factors are often analyzed as outcomes of enrichment programs. Recognizing the importance of psychosocial factors for high-potential students' future success, the *STEM Excellence and Leadership* extracurricular program integrated a psychosocial self-report measure into the identification process to provide additional information about students' psychosocial characteristics, including motivation, self-regulation, and student engagement.

The Current Study

The central aim of this study was to investigate the effectiveness of an expanded talent search model (Assouline & Lupkowski-Shoplik, 2012; Olszewski-Kubilius, 2015) as a way to address underidentification of rural students for gifted programming (Stambaugh, 2015). The talent search model uses above-level tests in specific domains (e.g., math and science). To address the underidentification of high-potential students in rural schools, we modified the talent search model in two ways. First, teachers were encouraged to identify a broader group of high-achieving students to form the talent pool. Second, the expanded process included the administration of a self-report survey measuring psychosocial skills.

The overarching question that guided our investigation centered on: *the likelihood that an expanded above-level testing model would effectively differentiate among high-achieving students from underresourced rural schools who were part of a broad, inclusive talent pool.* Secondary to the overarching question were questions concerning *gender differences* and *program participants' subsequent math and science achievement.*

We examined the following research questions:

Research Question 1: What is the relationship between talent pool students' above-level test scores and psychosocial indicators?
Research Question 2: What are the gender differences among talent pool students' above-level scores and psychosocial indicators?
Research Question 3: Do students' psychosocial indicators contribute to the identification process, after accounting for their performance on the four subtests of the above-level test?
Research Question 4: How do students' math and science above-level scores differ based on identification, gender, and subsequent program participation?

Method

Sample and Procedures

The study population draws from schools in the state of Iowa, a predominantly rural, Midwestern state. The investigators posted a general announcement describing the goals of the *STEM Excellence and Leadership* program, which specified the focus on rural schools. Then, the investigators used NCES locale codes to identify rural schools with students in Grades 5 to 9 (N = 180 schools). All 180 schools received an announcement inviting them to submit an application to participate in the project. Twelve districts applied and 11 were selected based on their: (a) demonstrated commitment to the program through the application process, which required a signed commitment of program-support from each school's central administration, (b) location (NCES-definition of rurality and distribution throughout the state), and (c) the district's free or reduced-cost lunch (FRL) status. Approximately 48% of the students in the aggregate of the 11 schools qualified for FRL (range was 23% to 70%). Because of confidentiality constraints, individual information about FRL was not available.

Teachers in each of the selected schools then notified all high-achieving students who earned scores at or above the 85th percentile on one or more of the tests on the *Iowa Assessments*, a grade-level achievement test. This group of students was drawn from the total population of rising sixth-grade students across the 11 schools (N = 1,146). These students were not required to participate in their district's gifted and talented program. Across the 11 schools, 219 of the students were notified based on their achievement test scores (108 males and 111 females) and completed both the above-level test and psychosocial self-report questionnaire at Time 1. These students (N = 219) comprise the *talent pool* sample (students with above-average or higher achievement on a grade-level test; approximately 19% of the population). Using locally determined benchmarks and recommended guidelines on the above-level tests and psychosocial questionnaires, a subsample of 151 students (n = 79 males and n = 72 females; 13% of the total population and 69% of the talent pool sample) was recommended by their teachers for the *STEM Excellence and Leadership* program and elected to participate.

The following year (Time 2), all students in the original talent pool sample (N = 219) were invited to retake the above-level test and psychosocial questionnaire. The initial talent pool was composed of students who completed either assessment at Time 1; however, there was a substantial attrition rate (30%) between Time 1 and Time 2. Taking into consideration the attrition rate, the *analytic sample* (n = 123; 58 males and 65 females) was composed of the talent pool sample of students who had complete data at both test administration time points.

Multivariate analyses on the original talent pool sample with complete data (N = 219; 108 males and 111 females) were conducted to examine Research Questions 1 to 3. Longitudinal analyses on the analytic sample (n = 123; 58 males and 65 females) were conducted to examine Research Question 4.

Measures

The measures were administered during the spring to high-achieving fifth graders (rising sixth-grade students) in the talent pool (N = 219; 108 males and 111 females). Tests were administered under standardized conditions. The results were shared with teachers during specialized summer professional development, which was a component of the program. At the beginning of the school year, teachers used the results from both above-level testing and the psychosocial self-report survey to recommend participation in the year-long 24-week extracurricular math and science program.

Above-Level Testing. ACT Explore (ACT, 2013), which includes tests in English, math, reading, and science, is composed of content developed for the average eighth grader and was administered as an above-level test to high-achieving rising sixth graders. The English test has 40 items, the math and reading tests have 30 items each, and the science test has 28 items. The format is multiple-choice and students' responses were recorded on a machine-scored answer sheet. All tests and answer sheets were returned to the researchers and sent to ACT for scoring. ACT (2013) reports that ACT Explore reliability coefficients and average standard of errors of measurement are weighted frequency distributions. Kuder–Richardson 20 (KR-20) internal consistency reliability coefficients for Form A, Grade 8 ACT Explore scale scores are English, 1.66; math, 1.71; reading, 1.44; and science, 1.53. Raw scores are converted to a scale score; scale score ranges are 1 to 25. Our analyses used students' scale scores.

Psychosocial Measures. Students completed ACT Engage (ACT, 2016a), an online self-report survey. ACT Engage is available for students in Grades 6 to 9, high school, and college. For this investigation, we used the survey developed for sixth–ninth graders. ACT Engage has 10 subtests designed to measure three broad areas: motivation, self-regulation, and student engagement. Although score reports for all 10 subscales are reported as percentiles (ACT, 2016a; Casillas et al., 2011), scale scores were used for our analyses. ACT Engage scale scores at, or as close as possible to, the 50th percentile for sixth graders are as follows (ACT, 2016b): Academic Discipline, 51; Commitment to School, 58.5; Optimism, 49.5; Managing Feelings, 43; Orderly Conduct, 48.5; Thinking before Acting, 40; Family Attitude toward Education, 58; Family Involvement, 50; Relationships with School Personnel, 40.5; School Safety Climate, 43.5. All the 10 ACT Engage scales are "relatively short (range = 9 to 12 items) and have good to excellent internal consistency reliabilities (Cronbach coefficient alpha range = .82 to .91; median = .87)" (ACT, 2016b, p. 16).

Analytic Approach

The purpose of this study was to evaluate the effectiveness of a modified and expanded identification process to identify high-potential rural students for an extracurricular STEM program. The process included teachers notifying high-achieving students, based on grade-level achievement, about the opportunity to take (a) an above-level test to determine aptitude (high potential) in math and science, as well as (b) a self-report survey that measured broad psychosocial attributes of students' motivation and engagement. To address Research Question 1, the association between students' aptitude and psychosocial measures, we first ran descriptive statistics on students' above-level test scores and psychosocial scores to determine the distribution of scores in the talent pool. We then ran Pearson correlations among the 4 ACT Explore and 10 ACT Engage scale scores to provide a description of the association between the above-level scores and psychosocial measures in the talent pool.

To address Research Question 2, gender differences in the above-level scores and psychosocial measures in the talent pool, we used one-way multivariate analysis of variance (MANOVA) tests. Before performing the multivariate tests, we evaluated the data with respect to assumptions of normality, linearity, outliers, homogeneity of variance, and multicollinearity. The data violated the assumption of normality and there were multiple outliers, thus we used Pillai's trace instead of Wilks's Lambda in the MANOVAs.

To address Research Question 3, the contribution of psychosocial scores on the likelihood of identification, we estimated logistic regression models to examine the multivariate associations among students' psychosocial measures and above-level scores on the likelihood they were identified for the program. We included gender as a covariate. Logistic regressions are used when the dependent variable is categorical in nature. In this study, the dependent variable is dichotomous and represents whether, *1* = student participated in program (N = 135) or *0* = student did not participate in program (N = 84). The specific logistic regression equation is as follows:

$$\ln\left(\frac{p}{1-p}\right) = \beta_0 + \beta_1\left(\text{ACT Explore}\right) + \beta_2\left(\text{ACT Engage}\right) + \beta_3\left(\text{Gender}\right)$$

The equation describes the association between students' ACT Explore and ACT Engage scale scores and the log-odds of being a participant in the program, while also accounting for gender. The log-odds ratio (OR) reflects the probability of participation compared with the reference category (i.e., students who did not participate in the program).

To address Research Question 4, the differences in math and science achievement, based on program identification and participation, we used a repeated-measures ANOVA with two between-subjects effects (identification and gender) and one within-subject effect (time) to test for main effects of identification, time, gender, and interaction effects among the three variables on students' math and science ACT Explore standard scores. All analyses were performed in PASW Version 23.

Results

Research Question 1: Association Between Above-Level Test and Psychosocial Measure

Descriptive analyses of the entire talent pool sample (N = 219) demonstrated that student performance on the above-level test, ACT Explore, approximated a normal distribution. The average ACT Explore scores for the talent pool students were found to be statistically significantly lower than the national average scale scores for eighth graders.

The distribution of 10 subscales for the psychosocial survey, ACT Engage, were all positively skewed. Table 1 presents measures of central tendency and normality for the ACT Explore and ACT Engage measures.

Bivariate correlations among the four ACT Explore scale scores and 10 ACT Engage scale scores at Time 1 are presented in Table 2. The four ACT Explore scores were all positively, moderately correlated; correlations ranged from r = .40 to .58. Among the 10 ACT Engage scores, the psychosocial measures were all positively correlated with the exception of commitment to school and family attitude toward school with orderly conduct; correlations ranged from r = .19 to .70. Between the ACT Explore and ACT Engage scores, there were more positive correlations with the psychosocial measures with English and reading compared with math and science scores.

Research Question 2: Gender Differences

The means and standard deviations for ACT Explore and ACT Engage scale scores for males and females are presented in

Table 1. Descriptive Statistics for ACT Explore and ACT Engage Scores With the Talent Pool.

	Total (N = 219)						Male (N = 108)		Female (N = 111)	
	Mean	*SD*	Min	Max	Skew	Kurtosis	Mean	*SD*	Mean	*SD*
ACT Explore, Time 1 (scale scores)										
English	14.64	3.18	9.00	24.00	0.58	−0.01	14.10	2.93	15.22	3.27
Math	14.29	2.52	4.00	24.00	−0.30	2.13	14.76	2.66	13.92	2.41
Reading	14.11	2.69	6.00	25.00	0.57	1.21	14.00	2.78	14.08	2.37
Science	16.45	2.28	6.00	24.00	−0.01	2.41	16.27	2.55	16.60	1.99
ACT Explore, Time 2[a] (scale scores)										
English	15.82	5.34	0.00	25.00	−1.41	2.73	14.81	5.36	16.75	5.18
Math	17.14	2.84	8.00	25.00	0.31	0.65	17.66	3.06	16.65	2.54
Reading	15.90	3.14	10.00	25.00	0.72	0.22	15.91	3.38	15.90	2.92
Science	17.73	2.90	8.00	25.00	0.03	1.47	17.62	3.43	17.82	2.33
ACT Engage, Time 1 (scale scores)										
Academic Discipline	54.44	5.83	26.00	60.00	−1.86	4.53	53.40	5.88	55.39	5.72
Commitment to School	57.47	4.79	22.00	60.00	−3.90	20.43	56.94	4.33	57.89	5.23
Family Attitude	56.96	3.50	43.00	60.00	−1.39	1.89	56.56	3.69	57.27	3.31
Family Involvement	50.74	7.90	20.00	60.00	−1.03	1.26	49.20	8.72	52.18	6.72
Managing Feelings	47.44	9.56	14.00	60.00	−0.90	0.34	45.18	9.55	49.42	9.22
Optimism	51.78	6.93	24.00	60.00	−1.20	1.50	51.33	6.98	52.07	6.92
Orderly Conduct	51.38	9.72	16.00	60.00	−1.30	1.18	47.93	10.08	54.54	8.29
Relationships with School Personnel	45.32	9.89	12.00	60.00	−1.09	1.18	43.40	10.31	46.90	9.23
School Safety Climate	48.26	9.03	14.00	60.00	−1.36	1.63	47.99	9.16	48.27	8.99
Thinking before Acting	43.77	8.57	16.00	60.00	−0.55	0.30	42.64	8.55	44.76	8.63

[a]Sample size for post–ACT Explore scores is n = 154 (74 males, 80 females; 30% attrition rate).

Table 2. Bivariate Correlations Between Time 1 ACT Explore and ACT Engage scores (N = 219).

Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1. English	—	.40**	.58**	.47**	.15*	.31**	.15*	.14*	.19**	.05	.12	.08	.06	.11
2. Math		—	.49**	.50**	.18**	.06	−.00	.07	.08	.05	.01	.05	.14*	.13
3. Reading			—	.58**	.23**	.17**	.14*	.12	.17*	.16*	.21**	.12	.18**	.20**
4. Science				—	.18**	.18**	.08	.01	.12	.10	.13	.06	.10	.18**
5. Academic Discipline					—	.47**	.41**	.43**	.50**	.55**	.41**	.42**	.27**	.44**
6. Commitment to School						—	.49**	.35**	.19**	.38**	.02	.29**	.15*	.16*
7. Family Attitude							—	.52**	.17**	.38**	.02	.25**	.06	.12
8. Family Involvement								—	.35**	.49**	.18**	.44**	.24**	.37**
9. Managing Feelings									—	.49**	.62**	.50**	.39**	.67**
10. Optimism										—	.27**	.51**	.37**	.48**
11. Orderly Conduct											—	.33**	.18**	.60**
12. Relationships with School Personnel												—	.66**	.43**
13. School Safety Climate													—	.32**
14. Thinking before Acting														—

$^{*}p < .05$. $^{**}p < .01$.

Table 1. A series of MANOVA tests were performed to determine whether there were significant differences in Time 1 ACT Explore and ACT Engage scores by gender. Attending first to ACT Explore scale scores, the multivariate result was significant for gender, Pillai's trace = 0.11, $F(4, 213) = 6.44$, $p < .001$, Cohen's $d = .63$. Based on a Bonferroni-adjusted alpha level of .0125 (adjusting for the four ACT Explore tests), there were significant gender differences for English scores, $F(1, 216) = 7.04$, $p < .01$; females have higher English scores than males. The effect size (Cohen's $d = .35$) was considered small.

For ACT Engage scores, the multivariate result was also significant, Pillai's trace = 0.11, $F(10, 208) = 4.67$, $p < .001$,

Table 3. Logistic Regression Analysis for Time 1 Above-Level Test Scores and Psychosocial Measures Predicting Program Identification (N = 219).

	Model 1		Model 2		Model 3	
	B (*SE*)	Odds ratio (e^{β})	B (*SE*)	Odds ratio (e^{β})	B (*SE*)	Odds ratio (e^{β})
ACT Explore Time 1						
Math			0.56 (0.11)	1.76***	0.58 (0.12)	1.78***
Reading			−0.06 (0.10)	0.94	−0.01 (0.11)	0.99
Science			0.40 (0.13)	1.49**	0.43 (0.13)	1.53**
English			0.06 (0.08)	1.06	0.06 (0.08)	1.07
ACT Engage, Time 1						
Academic Discipline	0.08 (0.04)	1.08			0.05 (0.05)	1.05
Commitment to School	0.01 (0.04)	1.01			−0.07 (0.05)	0.94
Family Attitude	−0.01 (0.06)	0.99			−0.04 (0.07)	0.96
Family Involvement	0.00 (0.02)	1.00			0.01 (0.03)	1.01
Managing Feelings	0.02 (0.02)	1.02			0.02 (0.03)	1.02
Optimism	−0.05 (0.03)	0.96			−0.02 (0.04)	0.98
Orderly Conduct	−0.03 (0.02)	0.97			−0.05 (0.03)	0.95
Relationships with School Personnel	−0.02 (0.02)	0.98			0.00 (0.03)	1.00
School Safety Climate	0.01 (0.02)	1.01			−0.04 (0.03)	0.96
Thinking before Acting	0.02 (0.03)	1.02			0.00 (0.03)	1.00
Gender	0.06 (0.31)	1.06	−0.12 (0.38)	0.89	−0.37 (0.44)	0.69
Constant	−0.60 (2.64)		−13.77 (2.10)		−7.60 (3.81)	
χ^2, prob > χ^2	9.34		93.96***		103.26***	
Pseudo-R^2	.04		.35		.38	

Note. *p < .05. **p < .01. ***p < .001.

Cohen's d = .94. Using a Bonferroni-adjusted α level of .005 (adjusting for the 10 ACT Engage subscales), statistically significant differences between male and female students included Managing Feelings, $F(1, 217) = 11.16$, $p = .001$, and Orderly Conduct, $F(1, 217) = 28.20$, $p < .001$. An inspection of mean scale scores indicated that females reported greater levels of the aforementioned ACT Engage scales compared with males. The effect sizes for the gender difference (Cohen's d = .46 to .70) was considered medium.

Research Question 3: Contribution of Psychosocial Scores on Identification

We further examined the association between above-level tests and psychosocial measures on the likelihood of identification, by using logistic regression analysis. We ran three models to examine: (a) main effects of the psychosocial measures, (b) main effects of the above-level test scores, and (c) joint effects of the psychosocial and above-level test scores. For each of these models, we include gender as a covariate. Table 3 reports the regression coefficients and ORs (e^{β}) yielded from the logistic regression models.

The ORs are interpreted as the change in odds for being a program participant given changes in the values of the independent variables. In Model 1, none of the psychosocial measures demonstrated a significant effect on predicting the likelihood of identification. In Model 2, math and science scores significantly predicted the likelihood of identification. Holding all the other variables at a fixed value, there was a 76% increase in the odds (OR = 1.76) of being a participant for one-unit increase in math scores. There was a 49% increase in the odds (OR = 1.49) of being a participant for one-unit increase in science scores. In Model 3, when looking at the joint effects, the effect of math and science on the odds of being a participant increased by 2% for math (OR = 1.78) and 4% for science (OR = 1.53). Across the models, gender had no significant effect on the likelihood of identification.

Research Question 4: Differences in Math and Science Achievement Based on Program Identification and Participation

We used repeated-measures ANOVA to examine the impact of program identification and participation on students' math and science achievement. Results are presented in Table 4. For math, there was a significant linear main effect of time; all students in the talent pool saw increases in their math achievement from Time 1 (M = 14.17, SE = 0.23) to Time 2 (M = 16.85, SE = 0.31). There were main effects for the two between-subjects factors, identification and gender. The

Table 4. Repeated-Measures Analysis of Variance Results for Math and Science Achievement by Identification and Gender (n = 123).

	Math		Science	
	F(1, 119)	d	F(1, 119)	d
Within-subjects effect				
Time	93.09***	1.77	13.89***	.70
Between-subjects effect				
Identification	30.21***	1.00	21.60***	.84
Gender	6.31*	0.46	1.23	.20
Interactions				
Time * Identification	2.70	0.28	0.00	.00
Time * Gender	0.49	0.00	0.95	.20
Identification * Gender				
Time * Identification * Gender	0.34	0.00	4.23*	.35

Note. *p < .05. **p < .01. ***p < .001.

estimated marginal mean of math scores for students who participated in STEM Excellence (M = 16.77, SE = 0.22) was higher than students who did not participate (M = 14.17, SE = 0.42); these mean scores collapse across Time 1 and Time 2. The estimated marginal mean of math scores for male students, regardless of participation and time, was higher (M = 16.10, SE = 0.34) than females (M = 14.93, SE = 0.32). There were no significant interaction effects among time, identification, and gender for math.

For science, there was also a significant linear main effect of time; all students in the talent pool saw increases in their science achievement from Time 1 (M = 16.56, SE = 0.21) to Time 2 (M = 17.38, SE = 0.29). Identification was the only significant between-subject effect for science. The estimated marginal mean of science scores for students who participated in STEM Excellence (M = 18.01, SE = 0.21) was higher than students who did not participate (M = 15.93, SE = 0.40); these mean scores collapse across Time 1 and Time 2. There was also a significant three-way interaction between time, identification, and gender for science. A comparison of the estimated marginal means (see Figure 1), shows that for females, nonparticipants, experienced greater increases in science achievement, whereas for males, participants experienced greater increases in science achievement.

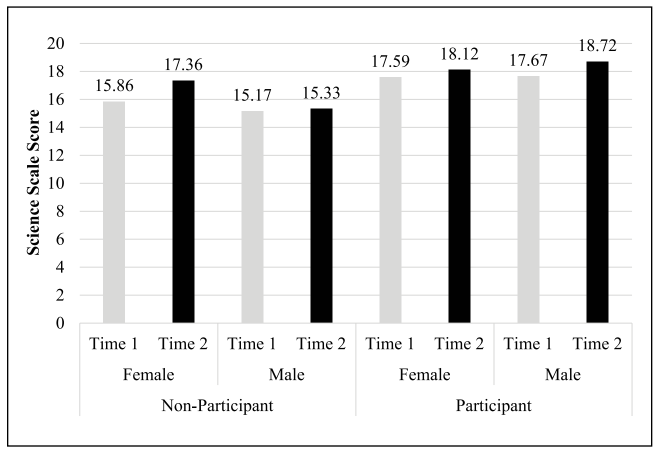

Figure 1. A comparison of science scale scores at Time 1 and Time 2 by gender and program participation.

Discussion

The purpose of this investigation was to examine the effectiveness of implementing an expanded talent search model (Assouline & Lupkowski-Shoplik, 2012) to differentiate among a broad and inclusive STEM talent pool of high-achieving fifth graders in rural schools. One of the major differences between the typical gifted program identification processes and the talent search model is the use of above-level subtests to discover students who are talented in specific content areas (Assouline & Lupkowski-Shoplik, 2012; Lee, Matthews, & Olszewski-Kubilius, 2008; Olszewski-Kubilius, 2015). A broader pool was desired to make the identification process and subsequent STEM extracurricular enrichment programming more accessible (Stambaugh & Wood, 2015) to rural students who typically may not be involved in either university-based above-level testing or gifted programming. Students in the talent pool of high achievers took an above-level test and a psychosocial survey to determine readiness for an accelerated STEM extracurricular program for rural middle school students.

Four research questions guided the evaluation of our assumptions about the expanded talent search model used in this study. First, the study examined the relationship between talent pool students' above-level test scores, psychosocial indicators, and gender (Research Questions 1 and 2). Research Question 3 looked at the contribution of psychosocial indicators to the identification process after accounting for performance on the four ACT Explore subtests. Finally, Research Question 4 aimed to determine differences in above-level test scores based on identification, gender, and subsequent program participation.

Results supported the use of the expanded talent search model with a broadly defined sample of high-achieving students. We operationalized high achieving by recommending to teachers that they generate a more inclusive talent pool by notifying students who earned scores on any subtest of a grade-level test at the 85th percentile or higher. The 85th percentile corresponds to one standard deviation above the mean on a standardized test, in other words, above average. Rather than the exclusive percentages of 3% to 5%, which is the case in many gifted programs (Callahan et al., 2014), 19% of the total population of rising sixth graders across the 11 schools, formed the talent pool sample and 13% of the total population (69% of the talent pool sample) formed the sample of participants. Moreover, these above-average students were challenged by the above-level test, but did not appear to be unnecessarily frustrated by the experience of taking a test with above-grade-level content.

Students' Time 1 performance on the above-level test approximated a normal distribution and supported our hypothesis that ACT Explore, which was developed for eighth graders and was used in this investigation as an above-level test, can effectively differentiate among the talent pool participants when used with fifth graders who scored > 85th percentile on a grade-level achievement test. Not surprisingly, students with higher Explore scores on the math and science tests were recommended for participation in the program. In other words, the above-level test *differentiated* among the talent pool of high-achievers and provided objective information about potential in specific domains. Even though the talent pool students earned scores that were lower than the eighth-grade average (eighth grade is the normative group for whom ACT Explore was developed), the scores were within the average range for eighth graders. The only statistically significant gender difference was for ACT Explore English scores among talent pool students at Time 1, with females earning higher scores.

The expanded talent identification process also included administration of a psychosocial self-report survey, ACT Engage (ACT, 2016a). The performance of the entire talent pool on all 10 ACT Engage tests was skewed positively suggesting already-strong skills in the 10 areas measured for all talent pool students. However, talent pool females had higher scores than males on the ACT Engage scales for Managing Feelings and Orderly Conduct. We interpreted this finding as an indicator that the high-achieving fifth-grade girls in this study, relative to the high-achieving fifth-grade boys, have comparatively stronger skills in managing their feelings and exhibiting orderly conduct, which suggests that girls fit well within traditional school norms. These results also suggest that high-achieving males might be at a relative risk for under identification in more typical gifted programs with selection criteria weighted toward behavioral compliance in schools.

All three models of the logistic regression analysis of the association between above-level tests and psychosocial measures on the likelihood of identification found that the psychosocial measures and gender had no significant effect on the likelihood of identification. One interpretation is that teachers were more likely to use the academic test scores (e.g., both the grade-level test for nomination to the talent pool and the subsequent above-level test results for recommendation into the program. An additional interpretation is that teachers used the ACT Engage data to be more inclusive in their selection process and selected students who demonstrated high academic potential regardless of their levels of motivation, self-regulation, or student engagement. Therefore, among this sample of high-achieving (above-average or higher) students, a broadened talent-search model may have served to limit gender bias in the identification process for a STEM extracurricular program.

When looking at the impact of program identification and participation, the results of the repeated measures ANOVA revealed a significant main effect for time in both math and science achievement. On average, students in the talent pool—regardless of program participation—improved their performance in the talent domains of math and science, as measured by the above-level test. This result was expected because all students experienced a year's worth of academic instruction. However, program participation affected the talent domains of math and science, albeit somewhat differently, especially with respect to boys and girls.

As mentioned, the mean growth in math was greater than the growth in science. Perhaps this is because students had more room to grow in mathematics. The main effect of identification showed that students who participated in the program had higher math scores at Time 1 and Time 2, compared with students who did not participate in the program. We interpreted these results as an indicator that the talent identification process effectively contributed to the identification of students with high math potential and subsequent program participation may have affected the development of that potential. The main effect of gender demonstrated that females in our sample started with a statistically significantly lower math score compared with males. This finding is meaningful because males maintained that advantage, especially those who participated in the program. Furthermore, our findings mirrored the Olszewski-Kubilius and Lee (2011) findings regarding stronger performance by talent search males on the ACT Explore math test.

There was a significant main effect for time in science, where students in the talent pool increased their science scores between Time 1 and Time 2. There also was a significant main effect for participation in the program. Similar to math, students who participated in the program had higher science scores at Time 1 and Time 2, compared with students who did not participate in the program. These results indicate that the talent identification process effectively aided in the identification of students with high science potential and the subsequent program participation developed that potential.

Unlike math, there was no gender main effect for science, but there was a significant three-way interaction between time, identification, and gender. Figure 1 reveals that the *nonparticipant* females had greater gains than the participants did, although both groups had gains in the expected direction. For boys, the gains for participation were in the expected direction; interestingly, the male nonparticipants had very slight improvement from Time 1 to Time 2. These results warrant further investigation on the possible gendered effects of participation in an extracurricular STEM program.

Regarding the growth of all talent pool students, regardless of participation, investigators noted that the extracurricular program instructors were typically the same teachers that students had during the day. We did not investigate the impact of professional development on the teachers' instruction during the traditional school day. However, because on average, regardless of program participation, students demonstrated growth, we assumed that this might have been—at least in part—due to improved instructional practices for high-ability students. Only an investigation with an experimental design would provide relevant data about the impact of professional development on student growth.

Limitations and Insights for Future Research

The investigation was limited to one state, Iowa, although the school districts were located across the state. This state is also homogenous in terms of ethnic and cultural diversity, which limits the generalizability of the findings for other rural populations. However, the students were in schools that were, on average, in communities with high percentages of students who qualify for FRL. Furthermore, information on students' FRL status was not available because of confidentiality; this is unfortunate because it would have been helpful to know if the talent pool students were representative of the district's FRL percentages.

The numbers of students were not evenly distributed across the 11 schools, which may minimize potential school effects in the identification process. For example, although the above-level and psychosocial tests were administered under standardized conditions, there may have been school-level effects related to the specific timing of the administration (morning vs. afternoon), or the educator proctoring the administration (a teacher, school counselor, or gifted education coordinator).

Expanding the talent search model to a broader group of high achievers (i.e., the top 13% rather than the top 5%), effectively found more students with high potential in STEM. Another aspect of expansion could include other types of measures to capture high-potential in broader domains such as inventiveness or computer science. One example could be the inclusion of a spatial ability test (Lubinski, 2010). Although the psychosocial measures in the current investigation yielded only a few statistically significant results relative to a contribution to the identification process, we recommend that future research attend to the varied ways in which students' psychosocial characteristics may contribute to achievement outcomes, such as in increased numbers taking high-level courses in high school.

This program included a professional development component, which incorporated information on giftedness and the interpretation of the test results. Future research might include the investigation of rural educators' understanding of gifted education concepts such as the talent search model, their attitudes toward working with high-potential students, as well as the impact of professional development related to enhanced pedagogical content knowledge. Providing curricular and pedagogical support to teachers is crucial to the success of the program and students. Professional development should also prepare teachers to use effectively the data from the assessment instruments so that they can establish an inclusive talent pool. By incorporating additional tests, offering professional development, and paying attention to underresourced schools, an expanded talent identification process can contribute to reducing the excellence gap by presenting new or alternative pathways to support the development of high-potential rural students and their teachers.

Summary

Students in underresourced rural schools are less likely to reach advanced levels of academic achievement compared with their urban peers, even when they demonstrate high potential (Kittleson & Morgan, 2012). High-potential rural students face barriers that reduce options for academic acceleration, putting them at-risk of becoming part of the "persistent talent underclass" (Plucker et al., 2015, p. 1). Plucker et al.'s report *Mind the (Other) Gap* (2010) identifies large gaps in academic achievement; they report that low-income, minority students are less likely to reach advanced proficiency on state and national assessments and that the gaps between the highest performing disadvantaged students and White, more affluent students, are significant. This discrepancy in the proportion of lower income students achieving the highest levels of academic performance is referred to as the excellence gap (Plucker et al., 2010). Economically disadvantaged high-potential students are less likely than economically secure students to retain high-achieving status throughout their schooling (Wyner, Bridgeland, & Dilulio, 2007). The excellence gap makes salient the consequences of allowing the talents of high-ability students to languish in underresourced schools. These encouraging results suggest that there are viable options for effectively identifying a broad talent pool of rural students in underresourced schools with STEM talents. If we aim to close the excellence gap, practices surrounding identification, curriculum, and instruction must be adjusted and evaluated so that policy can be developed or revised. Effective and early identification of high-potential and advanced programming in content-specific domains is a means to equalize opportunities for STEM education and career success, especially among economically disadvantaged, high-potential, rural students (Gira, 2007; Plucker et al., 2010).

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