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Profiles of Exceptionally Talented Students in Science, Technology, Engineering, and Mathematics (STEM): An Exploration Using Q Factor Analysis

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ABSTRACT

During the Cultivating Diverse Talent in STEM (CDTIS), studies were designed to identify and cultivate talent in potential innovators from low socioeconomic status (SES) and cultural groups underrepresented in the region: American Indian and Hispanic. Comparisons were made between those identified using conventional measures (CI) and those identified using performance assessments of problem solving (PSI) in STEM domains. In this study, using Q Factor Analysis, 43 students clustered on 13 factors, explaining 81.18% of the variance. Factors included high and low achievers; students from diverse groups; and 11 other clusters. Profiles are described and compared with profiles in other studies and theories. Implications for theory and practice include a paradigm shift from gifted child to talent development.

KEYWORDS

creative problem-solving; domain-specific assessment; identification; profiles of talented students; Q Factor Analysis; STEM; talent development; underrepresentation

Identifying and cultivating talent in the traditional areas of science, technology, engineering, and math (STEM) has become increasingly important in the 21st century. In 2010, the National Science Board (NSB) called for a concerted effort to stop importing talent from other countries and to develop a generation of STEM innovators: "individuals who have developed the expertise to become leading STEM professionals and perhaps the creators of significant breakthroughs or advances in scientific and technological understanding" (p. vii). As part of this effort, the NSB noted the importance and value of recognizing and cultivating these talents in all demographics of students. We have chosen to use the term exceptional talent rather than giftedness to situate our work clearly in the talent development paradigm with contributions from the differentiation paradigm (Maker, 2021, Maker, Pease, et al., 2022). Consistent with this perspective, research and practices resulting from the Discovering Intellectual Strengths and Capabilities while Observing Varied Ethnic Responses (DISCOVER) Projects (Maker, 2005, 2020b) were seen as the best approach for reaching both goals (Maker, 2020b).

The DISCOVER Projects (Maker, 2005, 2021) included two components: (a) development and validation of performance-based assessments in different domains, and (b) designing and evaluating a curriculum model consistent with the principles of talent development (Maker & Schiever, 2010). The elementary, middle, and high school forms of DISCOVER performance assessments had no gender or ethnic biases in studies involving Hispanic, American Indian, and White students (Sarouphim, 2001, 2002). The use of DISCOVER for identification changed the balance of underrepresented students in programs for exceptionally talented students in ways that reflected the ethnic distribution of students in the communities (Maker, 2005, Nielson, 1994). Students identified using these and measures derived from them were successful in special programs designed to serve them or in regular education programs (Reid et al., 1999, Sak & Maker, 2003). The DISCOVER curriculum model, an extension of the talent development framework and based on similar principles, was instrumental in increasing creativity when implemented at a high or middle level of fidelity (Maker et al., 2006, 2008).

Results such as these showed that instruments based on these principles and the definition proposed by Maker (1993a, 2020b) would have the potential to identify exceptionally talented students in STEM who could become innovators and entrepreneurs of the future. Measures also would not be biased against those from groups underrepresented in programs for gifted students in Arizona: American Indian, Hispanic, and from low socioeconomic status (SES) groups (Arizona Department of Education [AZDE], 2006, Snyder & Dillow, 2012). The Cultivating Diverse Talent in STEM (CDTIS) Project was designed to investigate these possibilities (Maker, 2020b).

A related purpose of the CDTIS research was to find out whether students identified as exceptionally talented

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in STEM by conventional methods (CI) and students identified by problem solving assessments (PSI) in different domains would have similar or different profiles. Conventional methods often include information aggregated across several domains as in the use of grade point average (GPA) or overall achievement (Subotnik et al., 2007; Tofel-Grehl & Callahan, 2017), while identification based on problem solving in different disciplines of STEM are domain-specific (e.g., life science, mechanical/technical, spatial analytical, mathematics). To find the commonalities in the two groups, the same data were collected on all students identified as exceptionally talented in STEM. The domain-specific problem-solving assessments created for this project were based on the same conceptual framework as the DISCOVER assessments.

Conceptual framework: Problem solving and a complex knowledge structure

The constructs of intelligence and creativity have been integrated into a definition of exceptional talent as consisting of three interacting components: (a) a highly integrated and interconnected knowledge structure, (b) ability and willingness to solve complex problems, and (c) varied types of problems, from well-structured and known to ill-structured and novel, in physical and natural science, technology, engineering, and mathematics in the most effective, efficient, elegant, or economical ways (Maker, 2020b). This framework includes both domain-specific and domain-general components (Amabile, 2013, Maker, 2021, Sternberg, 2000, 2010). Domain-specific components include skills and abilities that lead to exceptional performance in a domain (such as math or science) and domain-general creativity-relevant processes (intellectual and personal characteristics) cut across domains of creative performance (Amabile, 2013). Task motivation is interest in or attitudes toward a specific task (Amabile, 2013). A similar integrative view was proposed by Lubart and supported by his research: "Creative potential for a task is envisioned ... as the confluence of several distinct, but interrelated resources" (Lubart et al., 2013, p. 42). Resources include "aspects of intelligence, knowledge, cognitive styles, personality, motivation, affect, and physical and sociocultural environmental contexts" (p. 42).

An important component of this framework is *knowledge structure* rather than *knowledge* because underrepresented students seldom score in the top 1%, 5%, or 10% using measures of *knowledge* such as grades, achievement tests, and National Assessment of Educational Progress ([NAEYP]; Miller, 2004, Plucker et al., 2010). In research comparing experts and novices, especially in STEM, *knowledge structure* distinguishes experts from novices in domains (c.f., Bransford et al., 2000, Dogusoy-Taylan & Cagiltay, 2014). Within our framework, knowledge structure is measured by concept mapping (Maker & Zimmerman, 2020, Zimmerman et al., 2011). Students put concepts into a hierarchy, tell how they are connected, and give examples rather than answering questions with right and wrong answers. On concept maps, scores of students of color and students from low SES groups are not significantly different from scores of students from White, Asian, and middle/high SES backgrounds (Maker & Zimmerman, 2020).

Using assessments based on this conceptual framework enables researchers and practitioners to describe *dynamic profiles* of students rather than focusing on *static types*. Profiles are "dynamic, task- (or talent domain-) specific, and inclusive of many contextual variables rather than merely [as] a composite index based on several test scores or rating scales (Treffinger & Feldhusen, 1996, p. 186)." Many theorists and researchers have focused on types of gifted students rather than on profiles, often based on theoretical perspectives rather than empirical evidence. The examples that follow include both theoretical and empirical approaches.

Types and profiles

Types

Beliefs and research about types of gifted and talented students have changed, beginning with Terman (1905) who identified one type based on an IQ score of 130, but later separated successful from unsuccessful (Terman & Oden, 1959). The types studied most frequently and of continued importance, especially when considering underrepresented students, are achievers (ability scores and achievement scores are consistent) and underachievers (ability scores are high, but achievement is low) (c. f., McCoach & Siegle, 2003). Sternberg (2000) proposed three types of abilities (analytical, creative, and practical) while Gardner proposed eight types (1983, 1999): linguistic, logical-mathematical, interpersonal, intrapersonal, spatial, musical, bodily-kinesthetic, and naturalistic. Renzulli (1986) described two types: school house gifted and creative-productive gifted. Betts and Neihart (1988) proposed six types: successful, challenging, drop-outs, double-labeled, and autonomous learners. Recently, Sternberg (2020) proposed two types: transactional (identified as gifted and expected to do something in return) and transformational (they wish to make the world a better place).

In science education, two different approaches have been taken. Brandwein (1992), based on experience and research with the Westinghouse (now Intel) Science Talent Search, distinguished three types: general giftedness (high achievement and IQ), science proneness (high interest and high achievement in science, and skill in problem-doing), and science talent (ability to plan and complete investigations involving problems without known solutions). Similarly, Feist (2006a, 2006b), in studies of talent search finalists and members of the National Academy of Science, found that early involvement in active, original research was a more valid predictor of productivity and performance in STEM areas than intelligence and school grades. From a different perspective, Julian Stanley (1996), in the Study of Mathematically Precocious Youth (SMPY), used scores on out of level Scholastic Aptitude Tests, Mathematics (SAT-M) and Verbal (SAT-V) portions to identify students as gifted. Others who continued research related to the SMPY identified spatial as an essential underlying ability for STEM fields, noting that " . . . contemporary talent searches miss many intellectually talented students by restricting criteria to mathematical and verbal ability measures" (Wai et al., 2009, p. 827).

Profiles

Expanding research on creativity beyond that of Torrance (1990), focused on general creativity (high and low) in figural and verbal domains, Lubart et al. (2013) provide evidence that creativity requires domain-specific knowledge and skills, domain-general knowledge and skills, and task-specific abilities. They outline two creative thinking process clusters, divergent-exploratory and convergent-integrative, which are used in different domains such as verbal-literary, graphic, mathematical, social, scientific, and musical. Because of low correlations between creative potential scores in different types of tasks and/or from different domains and multiple interactions, they recommend development of "profiles" of creative potential with information about an individual's ability when compared with the average profile of a group.

Profiles are ways to describe strengths and challenges of students so they and others can design opportunities to develop talents and creative potential (Baum et al., 2014, Lubart et al., 2013, Maker, 2021, Maker, Pease, et al., 2022, Pease et al., 2020, Sternberg, 2000, Treffinger & Feldhusen, 1996). Our profiles included psychological traits (e.g., intrinsic motivation, attitudes toward and beliefs about science, self-esteem, interest in science), and general creativity because research on talent development has shown these characteristics are important in talent development (Feist, 2006a, 2006b, Lubart et al., 2013, Subotnik et al., 2011).

Empirical studies of profiles of exceptionally talented students

Some researchers have employed statistical analyses to identify profiles (Castejon et al., 2016, Cho et al., 2008, Ferrando et al., 2016, Kornilov et al., 2012). In two studies (Castejon et al., 2016, Cho et al., 2008), participants were selected using general indicators such as scoring in the top 10% on general mental ability, creativity, and academic achievement. They then administered assessments of other characteristics considered important such as grade point average (GPA), self-concepts, attitudes toward school, beliefs about their abilities, and learning strategies. In two studies (Ferrando et al., 2016, Kornilov et al., 2012), researchers used Sternberg's (2000) Aurora Battery consisting of subparts with items to measure analytical, creative, and practical ability and the domains of words, numbers, and images. Scores were averaged and a sample-based method was used to select the highest-scoring students in each of the ability areas (analytical, creative, and practical). Empirically based profiles were developed using latent-cluster analysis (Castejon et al., 2016), hierarchical cluster analysis (Cho et al., 2008), and Q Factor Analysis (Ferrando et al., 2016, Kornilov et al., 2012).

In the studies in which participants were selected based on general measures (Castejon et al., 2016, Cho et al., 2008), four profiles were identified: high achiever and cognitive gifted, creative gifted, gifted achievers, and cognitive gifted (Castejon et al., 2016) and full-bloomer, good achiever, fade-away, and late-bloomer (Cho et al., 2008). In the studies in which students were selected based on high scores in different types of abilities (Ferrando et al., 2016, Kornilov et al., 2012), 16 profiles were identified in one study (Ferrando) and 24 in the other (Kornilov). Profiles were characterized by different levels of ability in the three areas (analytical, creative, and practical), and when the stimulus domains were combined with general abilities, more profiles were identified (Kornilov).

Using methods to select participants in which levels of varied types and domains of abilities are included, rather than a score aggregated across measures, makes possible identification of profiles reflecting diverse talents, their combinations, and their complexity. The two studies in which Q factor analysis was a method of exploration (Ferrando et al., 2016, Kornilov et al., 2012) had results similar to those in our study.

Purpose and research question

This study was part of a program of research conducted during the Cultivating Diverse Talent in STEM (CDTIS) Project, in which students were selected to participate in internships in the laboratories of scientists on the campus of an R1 (research) university in the Southwest. The purpose of this study was to explore and identify the commonalities in the profiles of students identified as exceptionally talented in STEM. Thus, the research question guiding this study was, *What are the profiles of students identified as exceptionally talented in STEM?*

Methods

The project

The CDTIS project was a response to the National Science Board's (National Science Board [NSB], 2010) call for identifying potential innovators from all demographic groups. It was a collaboration across diverse departments at the university (Bio5 Institute, College of Pharmacy, College of Science, College of Education) and administrators in two public, one charter, and one Bureau of Indian Affairs contract school. An important purpose of the research was to determine the effectiveness of two types of methods for identifying exceptionally talented students in STEM, especially those from underrepresented groups (Maker, 2020b; Maker et al., 2022): *conventional methods* (conventionally identified, [CI]) and *problem-solving assessments* (problem solving identified, [PSI]). The CI group was selected using methods that had been part of the Keep Engaging Youth in Science (KEYS) project for many years and the PSI group was chosen using methods based on Maker's definition (1993a, 2020b). Both groups were invited to participate in internships. Following the internships, identified students and others at the schools were offered talent development opportunities, and some returned to campus as assistants (Wu et al., 2019).

After an interview in which they identified their interests, students selected for the 7-week internship program were matched with scientists, graduate student mentors, and laboratories where they worked on research projects beyond their high school experiences. They learned and practiced laboratory skills, and then worked in life science, pharmacy, agriculture, medicine, and neuroscience laboratories. They designed and carried out original studies with the assistance of mentors and scientists, then presented their research in poster sessions attended by mentors, scientists, parents, other students, and interested members of the university community. During the following school year, under the supervision of a university science professor and/or their science teachers, they continued their research, worked with peers in their local schools, or initiated new research based on their interests.

Selection of exceptionally talented students

To recruit students, the KEYS staff visited schools in the state and encouraged students to apply. Applications were submitted online and included required information: GPA, teacher letter of recommendation, and self-statement of interest. To select CI participants, a committee of university faculty members, the director of the program, and others with experience making selections chose students based on a combination of scores and information submitted.

To select PSI students, members of the education research team administered problem-solving assessments in all four partner schools: three on the American Indian reservation and one in a low SES urban area serving several ethnic groups, mainly Hispanic. No screening was used and all students in their junior year with signed consent forms were assessed using all six measures: life science performance (Zimmerman et al., 2020), life science concept maps (Maker & Zimmerman, 2020), mechanical/technical performance (Alfaiz et al., 2020), physical science concept maps (Maker & Zimmerman, 2020), spatial analytical performance (Maker, 2020), and mathematical problem solving (Bahar & Maker, 2020). An average of 308 students were assessed using each measure (ranging from 307 to 334). Profiles were created for all students across all assessments (Pease et al., 2020), and the team chose as many PSI students as possible given the funding available. All were ranked: students with the highest rating on six assessments, then five, and so on, so the team could consider all assessments and all levels of ratings.

After the two groups were chosen, PSI students provided the information used to select CI students, and CI students were assessed using the problem-solving measures. Students from both groups completed assessments of psychological traits (e.g., intrinsic motivation, attitudes toward and beliefs about science, self-esteem, interest in science), and general creativity because of research showing their importance in talent development (Feist, 2006a, 2006b, Lubart et al., 2013, Subotnik et al., 2011). Indicators of student performance were collected from teachers, including individual course grades and achievement test results in all content areas. Teachers also completed ratings of each student's characteristics.

Schools

Students in the CI group came from a variety of public, private, and charter schools in the state. Students in the PSI group came from the four partner schools. Because most schools in SESlow SES areas have fewer opportunities for exceptionally talented students, such as advanced placement courses, special opportunities, and participation in science and math competitions (Miller & Kimmel, 2012, NSB, 2010), we have illustrated differences in schools and contexts using percentages of students at the schools who received free and reduced-price lunches. The majority of CI students (15) came from schools in which 0% to 20%, 21% to 40%, or 41% to 60% of students received free and reduced-price lunches, while none of the PSI students came from schools in these three categories. All PSI students came from schools in which 61% to 80% or 81% to 100% of students received these lunches; while only 5 of the CI students came from schools in these two categories.

Participants

The 30 CI students who applied for admission were high school juniors (11th grade), accepted into the program, and agreed to participate in performance assessments and complete the other measures. They came from different schools, urban and rural, and varied ethnic and SES backgrounds. The 23 PSI students came from the four partner schools. The CI students were mainly White and Hispanic with parents who had college degrees; the PSI students were mainly American Indians whose parents had a high school education. Most students in both groups identified English as their primary language. Data about participants in the two groups are provided in Table 1: ethnicity, primary language, and highest level of parent education.

Instruments

Instruments included six assessments of problem solving and knowledge structure, a test of creativity, the achievement test administered in schools in the state, teacher ratings of student behaviors considered indicators of giftedness, intrinsic motivation, self-esteem, and attitudes toward science. In Table 2, descriptive information is provided for all instruments used in the study: name, purpose, samples of tasks, methods of scoring, scores and ratings obtained, and validity and reliability information when available. Information is provided for all instruments in table format to enable readers to reference and compare instruments easily.

Data collection

Administration

Performance-based problem-solving assessments (life science, mechanical/technical, and spatial analytical) were administered to groups of not more than five students by trained observers on the research team. Observers gave instructions, distributed materials, interviewed students and recorded their responses, and as a group (along with other observers) scored responses and assigned ratings. After each assessment was completed, observers reviewed students' performance: they listened to audio records of student interviews and transcribed responses, completed notes about each student in the group, and assigned tentative scores and ratings. When all observers had completed this process, they met to discuss students' strengths.

Table 1. Demographic data for conventionally identified (CI) and problem solving identified (PSI) participants

Variables	Groups	Conventionally Identified (CI)	Problem Solving Identified (PSI)	Row Totals
Gender	Female	13	13	26
	Male	7	10	17
Ethnicity	White	8	2	10
	Hispanic	6	5	11
	Native American	1	13	14
	Black	2	1	3
	Asian American	3	2	5
Primary Language	English	18	17	35
	Spanish	1	3	4
	Vietnamese	0	1	1
	Tagalog Austronesian	0	1	1
	Mai-Mai	1	1	2
Highest Level of Parent Education	Middle School	1	0	1
	High School	4	12	16
	Associates	2	2	4
	Some College	3	2	5
	Bachelors	3	3	6
	Masters	2	4	6
	Doctorate	5	0	5
Column Totals		20	23	43

Table 2. Description of instruments in factor analysis

Instrument & Reference	Purpose and Tasks	Scores, Scoring, and Ratings	Validity & Reliability
Life Science Performance Assessment (Zimmerman et al., 2020)	Purpose: Assess understanding of natural phenomena, including characteristics, relationships, and interactions. Tasks: (a) Make groups of either flowers or insects based on similarities, (b) Create an ecosystem and demonstrate connections and interactions.	Task 1: Each accurate grouping is given one point for each of the following: number of groups made (fluency), number of types of groups (flexibility), and details given about titles (elaboration). Sample-based originality scores: 1 for responses by 6–10%, 3 for those by 2–5%, 5 for responses by less than 2%. Task 2: A rubric containing criteria such as includes interactions, has a food chain, demonstrates interdependence among elements, has living and non-living things. Ratings: Observers reach agreement about a final rating, from 1 to 5 based on a combination of scores on both sections.	Interrater reliability is ensured because observers must reach agreement (Griffiths, 1996, 1997). Content validity was established through review by scientists and science teachers. Predictive and concurrent validity have not been studied.
Physical Science (Mechanical-Technical) Performance Assessment (Alfaiz et al., 2020)	Purpose: Assess understanding and application of the ways machines work, including gears, chains, and motors. Tasks: (a) make a gear box, (b) make one of the two vehicles shown in a picture, (c) make a machine of your own design.	Scoring: Observers review photographs of vehicles and machines as a group. Based on the rubric, they agree on ratings from 1 to 5 for all students in the groups. The rubric contains criteria such as the vehicle is stable, the machine or vehicle moves in many directions, has one or more motors to power the vehicle or machine, the design of the machine is different from the vehicle, the machine has chains to power the gears.	Interrater reliability is ensured because observers must reach agreement (Griffiths, 1996, 1997). Content validity was established through review by engineers and science teachers. Predictive and concurrent validity have not been studied.
Spatial Analytical Performance Assessment (Maker, 2020a)	Purpose: Assess ability to perceive the visual world accurately, analyze shapes and recreate them, and make transformations of images. Tasks: (a) Make a large rhombus-like figure with as many Tangram pieces as possible, (b) solve geometric puzzles of increasing difficulty with Tangrams.	Scoring: Observers ranked students based on the number of puzzles they completed, the number of pieces they used in the large shape. To assign overall ratings, Jenks (1967) natural breaks system was used. To use this system, scores of all students were ranked from highest to lowest, and the same rating was assigned for scores that were grouped together and were separated from other groups by at least three to five points.	Interrater reliability is ensured because observers must reach agreement (Griffiths, 1996, 1997). Concurrent validity: Sarouphim (2001) found significant correlations between scores on the spatial analytical assessment and the Raven in grades K, 2, 4, & 5 and across the total group. ($r = .409$, $p = .01$, $N = 257$). Predictive validity: Sak and Maker (2003) found that students rated 4 and 5 performed significantly higher than those with low scores on the Stanford 9 ($F = 7.02$, $p < .01$) and Arizona Instrument to Measure Standards (AIMS) math subtests ($F = 7.29$, $p < .01$) and end-of-year grades in science ($F = 4.05$, $p < .01$).
Life Science Concept Maps (Maker & Zimmerman, 2020)	Purpose: Assess understanding of the complexity of life science concepts and their interrelationships. Task: Students are given 18 concepts to map (e.g., *biodiversity, agriculture, ozone*) and are asked to make a hierarchical map. A focus question is posed: How does climate change occur?	Criteria: One point is given for *propositions* (number of valid connections), *hierarchy* (the number of levels of concepts), and *examples. Crosslinks*, the number of connections between major sections of the map are given scores ranging from 2 to 10 points based on their quality. Ratings: After scoring was complete, the research team members assigned overall ratings from 1 to 5 using Jenks Natural Breaks system (Jenks, 1967).	Interrater reliability and content validity agreement has been achieved among observers when using science concept maps (McClure et al., 1999, Stoddart et al., 2000).
Physics Concept Maps (Maker & Zimmerman, 2020)	Purpose: Assess understanding of the laws of physics such as forces and motion and Newton's 3 laws of motion. Task: Students are given 26 concepts related to forces and motion (e.g., *potential energy*, *velocity*, and *rocket launch*) and are asked to make a hierarchical map. A focus question is posed: What are the effects of forces on the motion of objects in your world?	Criteria: One point is given for *propositions* (number of valid connections), *hierarchy* (the number of levels of concepts), and *examples. Crosslinks*, the number of connections between major sections of the map, are given scores ranging from 2 to 10 points based on their quality. Ratings: After scoring was complete, the research team members assigned overall ratings from 1 to 5 using Jenks Natural Breaks system (Jenks, 1967).	Interrater reliability and content validity has been achieved among observers when using science concept maps (McClure et al., 1999, Stoddart et al., 2000).

(*Continued*)

Table 2. (Continued).

Instrument & Reference	Purpose and Tasks	Scores, Scoring, and Ratings	Validity & Reliability
Mathematical Problem Solving (Bahar & Maker, 2020)	Purpose: Assess ability to analyze problems logically, understand the underlying principles of systems, do mathematical calculations, and manipulate numbers, quantities, and operations. Tasks: (a) solve problems that have right answers and involve complex mathematical calculations, (b) make geometric patterns that follow a logical sequence, (c) create problems that fit a graph and then solve the problems.	Scoring: Two types of scores are assigned: accuracy and application of concepts. *Accuracy* is the number of correct answers across all problems. *Concept* scores, given only if the response is accurate, are assigned to application of mathematical concepts in creative ways such as making many different patterns, including different types of shapes in the patterns, and making complex patterns and problems. The two sub-scores are then combined to make a final score. Ratings: After scoring was complete, the research team members assigned overall ratings from 1 to 5 using Jenks Natural Breaks system (Jenks, 1967).	Reliability: Two research team members scored the assessments. Each scored 10% of all papers, and if they did not agree, they discussed the scores and reached agreement. In a predictive validity study, math scores at kindergarten accounted for 29% of overall variance in Stanford 9 Math (p = .033) and 39% in AIMS Math (p = .003) in grade 6 (Sak & Maker, 2003).
Test of Creative Thinking Drawing Production ([TCT-DP]; Urban, 2005)	Purpose: Assess integrated creativity. Task: Complete an incomplete drawing that includes several shapes inside a box and one shape outside the box. Students are told the artist did not finish the drawing and that no answers are incorrect.	Criteria: Fourteen criteria, including continuations, completions, new elements, humor and affectivity, and unconventionality are scored for each drawing. A range of zero to six points are assigned for each criterion and a total score calculated. Scoring: The total score was used in the analysis.	In various studies the interrater reliability was above r = .87.It has a high reliability for differentiation between the 25% highest and lowest achievers in both test forms (Chi-square = 33.54, C (corr.) = .92) as shown with a large Hungarian sample (N = 1100).
Arizona's Instrument to Measure Standards ([AIMS]; Arizona Department of Education, 2017)	Purpose: Assess student achievement in reading, writing, math, and science. Tasks: Multiple choice items in academic areas.	Scoring: Students are given a total score on each subtest: reading, writing, math, and science.	Cronbach's alpha, a measure of internal-consistency reliability, for the science sub-score ranged from .72 to .93 and was consistent across grade levels and race subgroups. Analysis of Differential Item Functioning (DIF) on all operational items indicated no item bias against different gender, ethnicity, and race subgroups,
Scales for Rating the Behavioral Characteristics of Superior Students ([SRBCSS]; Renzulli et al., 2002)	Purpose: Assess teacher perceptions of student characteristics in each of the following areas: learning, creativity, motivation, leadership, artistic, musical, dramatics, communication (precision), communication (expressiveness), planning, mathematics, reading, technology, and science. Tasks: Teachers rate students based on their perceptions of student competencies.	Ratings: Teachers gave ratings on a scale of 1 (low) to 5 (high) on each item in all 14 areas. Areas had different numbers of total scores. Scoring: Scores on each area were included separately in the analysis.	Factor analysis, alpha reliability, and criterion related validity were calculated by comparing fall teacher nominations with spring success. Validity: Confirmatory Factor Analysis – Four Factor Structure, X2 (371) = 1541.22, RMSEA = .07, TLI = .95, CFI = .95. Radialities: r = .95.
Children's Academic Intrinsic Motivation Inventory ([CAIMI]; (Gottfried et al., 2001)	Purpose: Assess intrinsic motivation, such as enjoyment, curiosity, persistence, difficult and challenging tasks. Tasks: Students rate each of the 122 items on a 1 to 5 scale indicating strongly agree to strongly disagree on items such as *I enjoy learning new things*. Questions are in 5 areas: Reading, Math, Social Studies, Science, and General.	Scoring: Points were assigned to each of the specific learning areas for a total score in each category. Each subject area contained 26 items; the General scare contained 18 items. The minimum possible score on any of the four subscales was 124, and the General score contained 18.	For internal consistency and test-retest reliability, coefficients were consistent across grade, sex and race. Coefficients ranged from .66 to .76 and .69 to .75 indicating moderately high stability.

(*Continued*)

Table 2. (Continued).

Instrument & Reference	Purpose and Tasks	Scores, Scoring, and Ratings	Validity & Reliability
Coopersmith Self-Esteem Inventory (McGrimmond, 2006; Prewitt Diaz, 1984)	Purpose: Assess 4 aspects of self-esteem (general self, social self-peers, home parents, and school academics). Tasks: Students complete 50 items, deciding whether the item is *like me* or *unlike me*. Examples of statements are *Things usually don't bother me* and *I find it very hard to talk in front of a group*.	Scoring: A final score was given based on the totals for *like me* and *unlike me* to the fifty statements indicating the various levels of self-esteem for each student.	The current literature The current literature has indicated that the SF-CSEI reported satisfactory reliability and construct validity (with Cronbach's alpha ranged from 0.68 to 0.77). Satisfactory reliability with Cronbach's alpha ranged from .68 to .77. The current literature has indicated that the SF-CSEI reported satisfactory reliability and construct validity (with Cronbach's alpha ranged from 0.68 to 0.77). The current literature has indicated that the SF-CSEI reported satisfactory reliability and construct validity (with Cronbach'saranged from 0.68 to 0.77)
Scientific Attitude Inventory II (Moore & Foy, 1997)	Purpose: Assess attitudes and beliefs about science. Tasks: Students respond to 6 opposing positive and negative attitude statements related to each of the 12 position statements, such as *Scientists are always interested in better explanations of things*, and *Scientific ideas can be changed*. Students tell if they strongly agree, mildly agree, are undecided, mildly disagree, or strongly disagree.	Scoring: The SAI II was scored by assigning point values to each of the attitude items in six categories for a total score in each category. Categories were *rationality, open mindedness, curiosity, aversion to superstitions, objectivity of intellectual beliefs* and *suspended judgment*. No total score was assigned.	Validity for the SAI II was based on the original judgments of a panel of judges regarding the attitude position statements, A split-half reliability coefficient of .805 was computed for the entire group of 557 respondents. Cronbach's alpha reliability coefficient was .781.

Concept maps, math problem solving, the creativity test, and other written assessments were administered in large groups by a member of the research team, with other members or teachers at the school as monitors. Instructions in manuals were followed closely. For concept mapping, students practiced making concept maps and then were asked to start their maps from general ideas or concepts and proceed to more specific ideas (Maker & Zimmerman, 2020). The math assessment was given in a similar way, with explanations of each section to make sure students understood the tasks (Bahar & Maker, 2020). Monitors did not give suggestions for content or answers, but made certain students followed directions.

Scoring

In Table 2, scoring procedures for all assessments are described. For instruments not developed during the project, assessment manuals were followed closely. For the performance measures, after each assessment, all observers reviewed the performance of all students assessed that day and reached consensus on ratings to ensure interrater reliability (Griffiths, 1996, 1997). Ratings were based on the problem-solving behaviors observed: 1 (*unknown*), 2 (*maybe*), 3 (*probably*), 4 (*definitely*), and 5 (*wow*). For concept maps and math, after individual items and sections were scored, Jenks Natural Breaks system (Jenks, 1967) was used to assign overall ratings. Using this procedure, total scores were ordered from highest to lowest, with the same rating given for scores clustered together and separated from other groups by at least 3 to 5 points. Students from similar schools (AI, rural and H, urban) were compared with each other (Bahar & Maker, 2020; Maker & Zimmerman, 2020).

Data analysis

Because the aim was to explore and describe clusters of characteristics (profiles) of students identified as exceptionally talented in STEM, Q factor analysis was chosen for data analysis. Q factor analysis is a powerful technique to investigate empirically distinguishable profiles in groups (Cattell, 1952, Kerlinger, 1986, Stephenson, 1953). Although researchers have seldom used it, Q factor analysis might extend the capabilities of researchers in the field of education for the gifted.

Because it can be used with small sample sizes, even single cases, when researchers have more items or variables than participants (Cattell, 1952, Kerlinger, 1986), profiles of rare and interesting gifted and creative students can be identified (Thompson, 2010).

Q factor analysis is commonly referred to as inverse factor analysis. It has been used to classify *person types* whereas R factor analysis is used to identify *dimensions of a construct* (Ferrell & Daniel, 1995). Although Q analysis is similar to the more common R analysis in that both are used for data reduction, they are different in many ways, specifically their methods and analyses. Q factor analysis involves qualitative methods in which researchers interpret the factors and "their description as perspectives" (Ramlo, 2016, p. 73). Similarly, Q analysis does not depend on generalizability: "a large number of persons on a factor is not required to lead to sufficient descriptions of each factor" (Ramlo, 2016, p. 81).

As suggested by researchers (Zabala et al., 2016), we followed this sequence of tasks: (a) forming the initial data matrix from raw data, (b) obtaining z-scores, (c) determining a proper method for extraction of factors (principal component analysis [PCA] or centroid), (d) determining a proper rotation method, (e) reviewing rotated factor loadings, (f) distinguishing statements, and (g) describing final factors.

Before the analysis, we transformed all scores to z-scores and transposed the data matrix. Next, principal-components analysis extraction with varimax rotation was selected to analyze the transposed matrix of the typologies on SPSS 26. Extraction was based on eigenvalues as suggested by Brown (1978). Although several researchers recommended extracting factors with eigenvalues greater than 1, different from R analysis, researchers have reached no consensus on the criteria for determining significant loadings in Q analysis. Ramlo (2016) and Brown (1978) attribute these inconsistencies to the fact that the number of factors, explained variance, and eigenvalues are not as critical for Q as they are for R, because the strength of Q analysis stems from interpretation of factors. Considering the diverse perspectives in determining factor loadings, we followed the suggestions of Brown (1978). We extracted factors with eigenvalues larger than 1.00: factors lower than this were not considered to be factors.

Results

The 43 students clustered in 13 factors; 81.93% of the total variance among students was explained. Each factor was a cluster of students. Rotated loadings, eigenvalues (1.71 to 3.34), percentage of variance, and cumulative percentage of variance are in Table 3. For example, after varimax rotation, the first factor explained 8.39% of the total variance with an eigenvalue of 3.34. Based on the analyses, we described profiles of students in each cluster. The largest cluster included twelve students and the smallest three students.

Developing descriptions of the factors

First, we examined the varimax rotated component matrix (Table 4) using correlations of + or − 0.400 as the criterion for including a particular student when describing a cluster. If students were in more than one group (Ferrell & Daniel, 1995), we included the student in the group with which he or she had the highest correlation with the factor unless correlations across factors were similar. In that case, and in the case in which a factor had only one student, we included other students already in another group. Most factors

Table 3. Q factor analysis results

	Unrotated Sums of Squared Loadings			Rotation Sums of Squared Loadings		
Factor	Eigenvalue	% of Var.	Cum. %	Eigenvalue	% of Var.	Cum. %
1	5.407	13.575	13.575	3.341	8.388	8.388
2	3.829	9.613	23.188	2.926	7.346	15.734
3	3.413	8.570	31.757	2.605	6.540	22.274
4	3.320	8.337	40.094	2.769	6.952	29.226
5	2.951	7.408	47.502	2.638	6.624	35.850
6	2.469	6.198	53.700	2.643	6.636	42.486
7	2.323	5.832	59.532	2.299	5.772	48.258
8	1.888	4.741	64.273	2.505	6.290	54.547
9	1.770	4.443	68.716	2.207	5.541	60.089
10	1.556	3.906	72.622	2.254	5.659	65.748
11	1.496	3.756	76.378	1.710	4.292	70.040
12	1.194	2.997	79.375	2.275	5.712	75.752
13	1.016	2.552	81.926	2.459	6.174	81.926

Table 4. Varimax rotated Q factor loading matrix

	F1	F2	F3	F4	F5	F6	F7	F8	F9	F10	F11	F12	F13
2014A030							−0.894						
2014A072			−0.315	0.602									
2014B003				0.568									
2014B009		−0.393								−0.659			0.332
2014B010		0.715											
2014B016									0.754				
2014C006	−0.352		0.443								0.436		0.339
2014C014			0.746										
2014D010				0.544									
2014D016	−0.423				−0.463	−0.468							
2014D028		0.418		0.408	0.312								
2014D052		−0.326		−0.527			0.413						
2014D061			−0.411			−0.374			0.345				
2014D063	0.756							−0.358					
2014E002			0.318					0.784					
2014E003								0.737					
2014E004			0.851										
2014E005		−0.550					−0.618						
2014E006											0.691		
2014E007											0.749		
2014E008				−0.726		−0.348							
2014E009						−0.508	−0.494						
2014E010					−0.804								
2014E011	0.552									−0.346	−0.444		
2015A006					0.613								
2015A012			−0.363								0.324		
2015A016	−0.324		−0.305	0.393					0.300				
2015B008												−0.873	
2015B013					0.428	0.444		−0.443					
2015C001	0.339	−0.475			0.302			−0.349				0.407	
2015C004										0.852			
2015C024	−0.473	0.388				−0.529							
2015C055						0.843							
2015C056		−0.705						−0.309					
2015C059	−0.864												
2015C070	−0.523			−0.378						−0.438			
2015E001													−0.901
2015E002			−0.330		−0.524								
2015E003		0.615											
2015E004									−0.857				
2015E005	0.432						0.473						
2015E006	0.300				0.319						−0.513	−0.408	
2015E007	0.582						0.344						

had students with both positive and negative correlations, so the direction of the correlation was considered when naming the factor and describing characteristics of students in that cluster.

Next, we looked at each student's z-scores on each instrument or demographic variable to determine common and contrasting characteristics. In R factor analysis, the z-scores are used mainly for normalizing the data. However, for Q factor analysis the z-scores also help to identify a student's relative position on each instrument or demographic variable (Zabala et al., 2016). At this step, we listed common traits, scores, and ratings within each cluster of students to visualize similarities and differences for each factor and across all factors, attempting to understand why a student correlated with a factor. Each author decided independently, then we compared analyses for similarities and differences following the recommendations of Kerlinger (1986), who suggested that if a difference in interpretation occurred, data within that factor should be examined, raw data that contained the "person factor" considered, and a final decision made based on correlations of the individuals with the factor. If questions remained about a particular factor, other experts in Q factor analysis were consulted. Finally, we wrote a summary of profiles of students in each cluster and compared all factors to clarify them.

Factor Names and descriptions

Names, number of students in the group with positive and negative correlations with the factor, and a brief description of each factor are provided in the following list.

(1) *High and Low Achievers*: (4+ and 4-) Students with positive correlations with the factor had

high academic achievement on GPA and state tests; those with negative correlations had low academic achievement on the same measures.

(2) *Students Whose Parents Had High and Low Educational Levels*: (3+ and 3-) Students with positive correlations had parents with Masters and PhD degrees while those with negative correlations had parents with a high school education.

(3) *Students With Different Primary Languages*: (3+ and 1-) Students with positive correlations identified English as their primary language and the contrasting student identified Spanish as her primary language.

(4) *Students With Strengths and Weaknesses in Math and Mechanical-Technical*: (5+ and 2-) Students with positive correlations had strengths in math and mechanical/technical while those with negative correlations had weaknesses in these areas.

(5) *Students From Diverse Ethnicities, Cultures, and Environments*: (2+ and 3-) The two students were American Indian (AI) and the three students were Hispanic (H). They came from different environments, rural (AI) and urban (H).

(6) *Students With High and Low Creativity*: (2+ and 3-) Students with positive correlations had high general creativity and high creativity on the subscores on life and physical science concept maps (measures of creative application of knowledge) while students with negative correlations had the opposite pattern.

(7) *High and Low Creative Problem Solvers in Life Science*: (2+ and 3-) The two students with a positive correlation had high scores on concept maps and performance assessments of life science problem solving, while the other three students had the opposite pattern.

(8) *Students With High and Low Motivation for Science*: (2+ and 1-) The two students with positive correlations had high motivation for science while the student with a negative correlation had low motivation for science.

(9) *Students Identified by Conventional (CI) or Problem-Solving Methods (PSI)*: (1+ and 1-) The most salient differences between the two students were their demographic profiles and school achievement. The CI student was Asian Indian whose parents had a master's or PhD, had a high GPA, high achievement, and positive attitudes toward science. The PSI student was American Indian, from a small school on the reservation with parents who had a high school education, had a low GPA, and low achievement in all areas.

(10) *Students With High and Low Self-Esteem and Discrepant Teacher Perceptions*: (1+ and 2-) The PSI student with a positive correlation had high self-esteem and positive teacher perceptions of ability, while the two CI students had low self-esteem and were perceived negatively by their teachers. In all three cases, teacher perceptions of students' abilities did not match their scores.

(11) *High and Low Creative Problem-Solvers in Life Science and Spatial Ability*: (3+ and 2-) Students with a positive correlation had high scores in life science and low scores on spatial analytical performance; those with low scores in life science had high spatial analytical scores.

(12) *High and Low Spatial Analytical Problem Solvers*: (1+ and 2-) The student with a positive correlation had an average score on the spatial analytical assessment while the other two students had high ratings: completing more puzzles in the time allotted. In mechanical/technical problem solving, performance of all three students was similar.

(13) *High and Low Achievers With Positive and Negative Attitudes Toward Science*: (2+ and 1-) The two AI students with positive correlations had low achievement in all areas, negative attitudes toward science, and parents with a high school education, while the Arabic/Hispanic student with a negative correlation had high achievement in all areas except writing, parents with a bachelor's degree, and positive attitudes toward science.

Discussion

Comparison of types and profiles in our study and other types in the literature

School achievement (F1) is a common way to differentiate types; our first factor had clear patterns of high and low achievers. Our profiles and those of others (c.f., Castejon et al., 2016, Cho et al., 2008, McCoach & Siegle, 2003) were different because we did not identify *underachievers* and *achievers*, which would have required comparing ability scores with expected achievement levels.

Another pattern is high and low creatives (c.f., Betts & Neihart, 1988, Castejon et al., 2016, Ferrando et al., 2016, Kornilov et al., 2012, Lubart et al., 2013, Renzulli, 1986, Sternberg, 2000, Torrance, 1990, Urban, 2005). We used only one measure of *general* creativity, but had measures of *domain-specific* creative problem solving in six assessments across domains: mathematics, life science concept maps and performance, physical science concept maps and mechanical/technical performance, and spatial analytical performance (Maker, 2020b). Inclusion of domain-related measures of creativity probably contributed to identifying three factors (6, 7, and 11) in which profiles of students included creativity. One group (F6) had high- and low-general creativity as well as creativity in concept mapping, another group (F7) had high and low creativity in life science in both concept maps and performance, and the third group (F11) had high and low creativity in life science demonstrated in both assessments of the domain. Another difference between students in F7 and 11 was parent level of education. The highest level of parent education was high school for the high creatives and master's and PhD for the low creatives on F7 and 11.

Another distinction made in measures of ability and achievement and in theoretical discussions of talent domains is between quantitative (mathematical), verbal, and spatial abilities (Stanley, 1996, Wai et al., 2009). We found only one factor (4) with students whose profiles were different in mathematics. Students high in mathematics also had high scores on mechanical/technical performance. Although in preliminary analyses, math and mechanical/technical were not significantly correlated ($r = 0.137$, ns), we found a significant correlation between spatial analytical and mechanical/technical performance ($r = 0.254$, $p = .01$). However, both spatial and mathematical are abilities underlying mechanical/technical performance, which is related to the professional domain of engineering. Students must see how different three-dimensional parts fit together to make a gear box, a vehicle, and a machine that moves (Alfaiz et al., 2020). All abilities on this factor involve the logical skills in mathematics and skills of recognizing and manipulating patterns, components of spatial ability.

Two other related characteristics, motivation and attitudes toward science, were aspects of profiles of students in F8 and 13. High motivation and positive attitudes toward school were characteristics of the *successful* type described by Betts and Neihart (1988) and the *high-achiever* group identified by Castejon and colleagues Castejon et al. (2016). Low motivation and negative attitudes were traits of the *dropouts* described by Betts and Niehart (Betts & Neihart, 1988) and the *cognitive-gifted* group identified by Castejon and colleagues (Castejon et al., 2016). In our study, high motivation and positive attitudes toward science were characteristics of students whose parents had a high level of education (master's or PhD) while low motivation and negative attitudes toward science were characteristics of students whose parents had only a high school degree. Students were from different cultural and economic groups. Students from White and Arabic cultures had high motivation and positive attitudes toward science; students with low motivation and negative attitudes toward science were American Indians from low SES groups.

Four factors (2, 3, 5, and 9) were defined mostly by demographic characteristics. Three were significantly different in CI and PSI students: those defining F2 (parents with high- and low-educational levels), those defining F5 (diverse ethnicities, cultures, and environments), and F9 (CI and PSI students). These results are consistent in two studies, one using chi square analyses (Maker, 2020b) and this study using Q factor analysis. No other studies of profiles included demographic characteristics of students in their analyses except studies of achievers and underachievers (c.f., McCoach & Siegle, 2003). Authors who proposed theoretical types also did not include demographic traits, showing that a contextualist worldview (Ambrose, 2000) was not considered. However, in many studies differences have been found between percentages of students of color and students from mainstream, high- to middle-income groups identified using methods based on the gifted child paradigm in which the *context* of talent development was not taken into account in the identification process (c.f., Ambrose, 2013, McBee, 2010, Miller, 2004, Plucker et al., 2010).

Interestingly, only one factor was clearly related to the selection of students by conventional versus problem-solving assessments (F9). Rather than being separated by performance on different types of assessments, they were separated by demographic characteristics and school achievement: high and low GPAs, ethnicity (Asian Indian versus American Indian), parents with high- and low-levels of education, and attitudes toward science. These differences, except for attitudes toward science, were identified as significant differences between the two groups in another study (Maker, 2020b).

Limitations

In this study, 43 students and 67 variables were included in Q factor analyses, giving a 1.56 to 1 ratio of variables to people. Although the most accepted statistical consideration is to have more variables than participants (Ferrell & Daniel, 1995), some recommend a 2 to 1 ratio of variables to people to increase trustworthiness (Thompson, 2010). Because our analysis did not indicate any data saturation or participants who were unwilling to provide additional responses, the ratio of variables to people was in the acceptable range.

A limitation is that some students did not have complete achievement test data. In some schools, science assessments were not administered, and in some cases, students took nationally normed tests instead of the state test, so their data could not be included. Other missing data were teacher ratings of student characteristics (Table 2).

Educational implications of the results

An essential question is *How can we use these results to recognize and cultivate exceptional talent in STEM?* The Cultivating Diverse Talent in STEM (CDTIS) project, of which this study was a component, was designed to (a) find and develop potential STEM innovators, and (b) in all demographics of students. We believe the project was successful, but additional research is needed. For instance, both CI and PSI students were successful in the internship program (Wu et al., 2019), and teachers believed they were successful in programs to serve them in partner schools (Maker, 2016). However, long-term follow-up studies are needed. Based on our studies (c.f., Maker, 2020b) and practices (Pease et al., 2020) during and after the CDTIS project, we can make recommendations for recognizing and cultivating exceptional talent in STEM.

Recognizing exceptional talent in STEM

The number of factors and their complexity demonstrate the importance of using multiple indicators of exceptional talent and considering demographic characteristics. Regardless of students' patterns of school achievement, GPA, motivation, attitudes toward science, self-esteem, general creativity, or teacher perceptions of their learning and behavioral characteristics, most would have been identified by the assessments of (a) a highly integrated and interconnected knowledge structure (Maker & Zimmerman, 2020), (b) ability to solve complex, and (c) varied types of problems (creative problem solving) (Maker, 2020b, 2021). Students' abilities were demonstrated in different domains, such as life science concept maps (Maker & Zimmerman, 2020) and performance (Zimmerman et al., 2020), physical science concept maps (Maker & Zimmerman, 2020) and mechanical/technical performance (Alfaiz et al., 2020), math (Bahar & Maker, 2020), and spatial analytical performance (Maker, 2020a).

Students had different profiles within these areas: some had an excellent basis in domain-specific conceptual understanding and knowledge while others' strengths were demonstrated in performance on hands-on assessments (life science, spatial analytical, and mechanical/technical) rather than in written assessments (concept maps and math). Use of these types of indicators is consistent with Wallach's (1976) recommendation that "we should rely not on tests, but on samples of professional competencies themselves (p. 57)." However, Wallach also recommended that scores on achievement, creativity, and intelligence tests be used to screen out those with the lowest scores. We found that some of the students with the lowest achievement scores and low GPAs were some of the best creative problem solvers (Maker, 2020b, Maker, Pease, et al., 2022). Thus, we recommend using samples of professional competencies with many students, especially those from underserved groups: low-income families, non-mainstream cultures, with native languages other than English, and with parents who do not have a high level of education (Maker, 2020b, Sarouphim, 2002).

The two CI students who would not have been identified using problem-solving assessments were selected based on their GPAs, teacher recommendations, and self-statements. They did not demonstrate a high level of creative problem-solving abilities in more than one area. No students in the PSI group had high scores on only one or two of the six assessments. They demonstrated creative problem solving or a highly integrated and interconnected knowledge base in more than one talent area.

Another pattern across several factors is the underlying presence of spatial analytical ability, an area gaining attention in STEM fields (Anderson, 2014, Wai et al., 2009). Spatial ability was defined by Lohman (1994) as "the ability to generate, retain, retrieve, and transform well-structured visual images" (p. 1000). It is important to STEM because individuals with this ability are "capable of moving engineering and physical science disciplines forward" (Wai et al., 2009, p. 817). Spatial ability also is essential in life sciences and math, especially if a more inclusive definition, such as the one used to create the DISCOVER spatial analytical assessment is used: perceiving the visual world accurately (noticing patterns in leaves, flowers, and other natural phenomena), making transformations or changes, and re-creating aspects of one's visual experience even when the physical stimulus is not there. These aspects of spatial ability are similar to the core capacities listed by Gardner (1983, 1999).

The only factor in which spatial analytical ability was the main component was F12. However, it was present in five other factors, as a trait in students either negatively or positively correlated with the factor. Spatial analytical ability as defined by Lohman (1994) may be important in physical sciences, but as defined in this project, it is an ability underlying all areas of STEM (Maker, 2020a). It also may be important in assessments of students of color from low SES groups who may not score in the top percentages on measures of achievement such as GPA, standardized tests of achievement (Miller, 2004, Plucker et al., 2010) or standardized tests of ability such as the SAT, which include only verbal and quantitative items (Wai et al., 2009). On the spatial analytical assessment in this research, students of color from low SES groups had consistently higher scores than students identified by conventional methods (Maker, 2020a).

Clearly, students identified by two different sets of criteria did not fit into two groups. Reducing differences in exceptionally talented students in STEM to conventionally-identified and unconventionally-identified is too simplistic, especially when information about other characteristics important in development and expression of talent, such as personality, motivation, and self-perceptions, are considered (Feist, 2006a, 2006b, Subotnik et al., 2011). However, based on our results, we recommend that characteristics such as motivation or personality not be used to screen out students. Many students have low motivation or negative attitudes toward science or math because of the way it has been taught rather than low motivation in general. Using Brandwein's (1992) description of *problem-doing*, *problem-finding*, and *problem-solving*, many exceptionally talented students probably have experienced only *problem-doing*; thus, they are not motivated to do well in laboratory experiments. In this project, students who experienced first-hand the excitement of cutting-edge research expressed their belief in the value of the program for their future goals (Wu et al., 2019).

An important aspect of student selection is the crucial role of teacher recommendations. As in the use of conventional methods for selection of students for the internship program, teacher recommendation often is a factor in the screening and identification process for students to be tested or deciding which students to accept into a special program (c.f., Subotnik et al., 2007). In our study, discrepancies were found between teacher perceptions of students' abilities and the students' actual performance, especially on F10. Teacher perceptions, especially perceptions of teachers from a culture or SES different from the student, should not be used to narrow the pool of students to be assessed using measures of creative problem solving.

At least three influences on discrepancies between teacher perceptions and student performance have been identified: (a) teachers often have overall perceptions of students as being *competent* or *not competent* rather than as having strengths and weaknesses (e.g., giving either ratings of all 5s or all 1s) even when given lists of characteristics to rate in multiple categories; (b) teacher perceptions of students' abilities are limited because they do not permit or encourage thinking, problem-finding, and problem solving, which includes identifying a researchable problem and designing experiments to find solutions (Brandwein, 1992); (c) teachers often have negative perceptions of students who are creative (Westby & Dawson, 1995); and (d) teachers' goals for students may not be compatible with the students' goals, resulting in lack of motivation to reach goals set by their teachers (McCoach & Siegle, 2003).

Students who are creative problem solvers may think differently from what their teachers perceive as important, appropriate, or accurate and are not recommended by their teachers even though creativity may be more important to productivity and performance in STEM areas than intelligence and school grades (Feist, 2006a, 2006b, Milgram & Hong, 1993). In research on Problem Based Learning (PBL) and REAPS, students whose talents had not been noticed were identified as gifted during their *engagement* in solving the problems that were *relevant* in their lives and communities (Gallagher & Gallagher, 2013, Riley et al., 2017, Webber et al., 2018).

Cultivating exceptional talent in STEM

Integrating the two components of talent development, *relevance*, and *engagement* (c.f., Iyengar et al., 2017, Maker, Pease, et al., 2022, Riley et al., 2017, Webber et al., 2018, Wu et al., 2019), and using the principles of focusing on talents and strengths, providing varied opportunities, and assisting students in making choices (c.f., Maker, Pease, et al., 2022, Pease et al., 2020, Wu et al., 2019) offers guidance in cultivating exceptional talent in students with the varied profiles identified in this research. In the CDTIS Project, we focused on two types of talent development programs: Real Engagement in Active Problem Solving (REAPS) and internships. Both have research demonstrating their effectiveness with students with varied profiles. REAPS (c.f., Maker, 2016, Maker, Bahar, et al., 2022a, Riley et al., 2017, Webber et al., 2018) was used in science classes in partner schools. Internships (c.f., Fraleigh-Lohrfink et al., 2013, Porter, 2017) were provided on campus and in partner schools (Wu et al., 2019).

REAPS is a combination of four evidence-based approaches with problem solving as a focus. Problem Based Learning (PBL) contributes an emphasis on solving real-world problems in small groups representing stakeholder groups with different values, interests, and perspectives; Thinking Actively in a Social Context (TASC) provides a step-by-step process alternating between divergent-exploratory and convergent-integrative thinking; DISCOVER gives guidance in selecting problems of varied types, from closed to open-ended; and the Prism of Learning helps teachers integrate multiple types of general capabilities (e.g., creativity, memory, intuition, metacognition, reasoning and logic) and multiple specific abilities (e.g., auditory, bodily/somatic, emotional/intrapersonal, linguistic, mathematical, mechanical/technical, moral/ethical/spiritual, scientific/naturalistic, social/interpersonal, and visual/spatial).

When educators use the REAPS model, they use profiles for differentiation.

- Students can be in groups based on similar characteristics to strengthen their talents and enable them to learn from each other. They can be in groups according to different strengths, particularly to learn to appreciate contributions from those with different talents. Diverse groups can be based on factors such as high and low achievement (F1 and F13), creativity (F6), and talents in different domains (life science, F7 and F11; math, F4; spatial analytical, F11 and F12;; and mechanical/technical, F4). Varying groupings over time is important: sometimes together based on similarities and other times, differences.
- Problems for investigation can be based on different contexts of students. For example, in this study, the AI students from the rural area (F5) probably would be more interested in a problem such as desertification (Maker, 2016) because of its effect on their lives. The Hispanic students from the urban area might be more interested in plastic pollution because of the failure of recycling efforts.
- Profiles can be used to assign students to different stakeholder groups based on either extending their strengths or helping them develop knowledge and skills in other areas. In the desertification problem, stakeholder groups included (a) farmers, ranchers, and sheepherders; (b) the grazing committee; (c) local residents; and (d) the Environmental Protection Agency (EPA). If placed in groups according to potential interest and knowledge about the problem, students from the rural area could represent farmers, ranchers, and sheepherders; students from the urban area could represent the EPA (F5). If placed according to need to develop understanding of a different perspective, students from the urban area could be farmers, ranchers, and sheepherders while students from the rural area could represent the EPA.

When cultivating talent using internships, methods employed in the CDTIS Project can be implemented. Students who have all profiles can be interviewed to determine their interests and placed in internships that match their interests even if profiles of abilities are different from interests. However, students, especially those with low achievement, can be encouraged to choose internships in their areas of strength. In the CDTIS project, all students participated in workshops to develop laboratory safety and other skills needed.

Profiles can be used to select mentors and provide support needed for success. If, for instance, a student has low achievement (F1 and F13), support might involve identifying or providing seminars to increase knowledge and understanding of important concepts in content areas (F7, F11, and F13; and if a student has low creativity (F6), support might include introduction to and practice of creative thinking skills. Students with different primary languages (F3) can be placed with a bilingual mentor to encourage them to identify concepts and compare cultural components in both languages. Students with low self-esteem (F10) can be encouraged to identify their strengths and other positive aspects of their performance during the internship.

In a study of the perceptions of students who participated in internships, the core theme was "active involvement in problem solving inspired and motivated students with exceptional talent (Wu et al., 2019, p. 484)." Identification of this theme is consistent with Brandwein's (1992) conclusion that students talented in science need to be involved in problem-finding and problem-solving and Feist's (2006a, 2006b) finding that early participation in original research was a significant predictor of later science achievements. Within this overall theme, three categories of responses were identified: academic initiative and engagement, transition preparation, and practical skill development (e.g., self-management, leadership). From this research, one can see that participation in the summer internship program and subsequent experiences during their last year of high school gave students from underrepresented groups the skills, confidence, and motivation to pursue careers in STEM, thus contributing to changes in representation of culturally and economically diverse individuals in the workforce.

Conclusion

The number, diversity, and complexity of profiles of students identified as having exceptional talent in STEM demonstrate the need for a paradigm shift in selecting students for special opportunities in STEM, based on a talent development perspective with a balance of world views rather than the gifted child paradigm (Maker, Pease, et al., 2022). A simple change is to use individual grades in math, life sciences, and physics rather than grade point averages, recognizing that students' interests and strengths are different in different content areas within STEM. Two changes that would achieve better results but are more expensive are to (a) use samples of professional competencies such as creative problem solving in the domains involved, and (b) assess students' levels of expertise rather than their memory and knowledge of facts, methods, and principles. These two changes incorporate an organicist and contextualist world view into the talent development paradigm (Ambrose, 2000). This shift would result not only in recognition of students with potential to become STEM innovators, but also in finding students from all demographic groups, including those usually underrepresented in STEM (Ambrose, 2013, Maker, 2020b; Maker, Pease, et al., 2022).

Today's students need a plethora of skills to be successful in our rapidly changing world (Lubart et al., 2013, NSB, 2010). Such principles as building on strengths, honoring interests and choices, solving real-world problems, and the wisdom to make sustainable change, locally and globally, are what we advocate for exceptionally talented students. Education, along with the integration of technology and an emphasis on diverse environments, can propel students' desire and motivation to address their own and others' needs.

Profiles are not static. They are descriptions of each student's talents and abilities *at this point in time*. Profiles are planning guides. Focusing on strengths in different domains and including important traits such as culture, parent and home influences, levels of achievement, and motivation in school are guides in helping students identify opportunities that fit their goals and needs. When students with passion and interest are given opportunities aligned with their goals, interests, and perceived needs, they can develop the wisdom needed to apply their intelligence, creativity, and knowledge for the common good while balancing their own, others', and the environment or culture's interests; and to consider the long- and short-term impacts of solutions while infusing positive ethical values into their actions.

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