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EXTENDING SANDRA SCARR'S IDEAS ABOUT DEVELOPMENT TO THE LONGITUDINAL STUDY OF INTELLECTUALLY PRECOCIOUS YOUTH

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Sandra Scarr has devoted her career to bringing the science of human individuality to bear on lifespan developmental issues (Scarr, 1992, 1996; Scarr & McCartney, 1983). Shining a light on the science of human individuality and the differential outcomes revealed by the study of human psychological diversity has not always been easy (Scarr, 1992, 1998), but it has almost always been useful for both applied and basic psychological science (Lubinski, 1996, 2000; Underwood, 1975), as well as for developing meaningful public policies focused on changing human behavior (Scarr, 1996). Still, the psychological import of valid measures of human individuality and the scientific knowledge gleaned by assessments thereof are routinely denied or neglected. In this chapter, our objectives are twofold. First, we will document the extent to which findings about human individuality are frequently dismissed or ignored in the social sciences, and how this hobbles the identification and development of truly exceptional human capital and modeling extraordinary human accomplishment. Second, we outline the usefulness of Scarr's ideas about niche building and selection (Scarr, 1996; Scarr & McCartney, 1983), and how the study of environments from a psychological perspective informs the creation of more optimal learning opportunities for students with exceptional abilities (Benbow & Lubinski, 1996; Benbow & Stanley, 1983; Benbow & Stanley, 1996; Stanley, 2000). Doing so simultaneously affords insight into their lifelong learning.

MEASURING THE FULL RANGE OF HUMAN INDIVIDUALITY

In Thomas L. Friedman's (2005) excellent and widely read *The World is Flat*, the saga of how Bill Gates established the Microsoft Research Center in Beijing, China, is detailed:

Kai-Fu Li is the Microsoft executive who was assigned by [Bill] Gates to open the Microsoft research center in Beijing. My first question to him was, "How did you go about recruiting the staff?" Li said his team went to universities all over China and simply administered math, IQ, and programming tests to Ph.D.-level students or scientists. "In the first year, we gave about 2,000 tests all around" From the 2,000, they winnowed the group down to 400 with more tests, then 150, "and then we hired 20." They were given two-year contracts and told that at the end of two years, depending on the quality of their work, they would either be given a longer-term contract or granted a postdoctoral degree by Microsoft Research Asia. ... Of the original twenty who were hired, twelve survived the cut. The next year, nearly four thousand people were tested. After that, said Li, "we stopped doing the test. By that time we became known as the number one place to work, where all the smart computer and math people wanted to work ... We got to know all the students and professors. The professors would send their best people there, knowing that if the people did not work out, it would be their credibility [on the line]. Now we have the top professors at the top schools recommending their top students. A lot of students want to go to Stanford or MIT, but they want to spend two years at Microsoft first, as interns, so they can get a nice recommendation letter that says these are MIT quality." Today Microsoft has more than two hundred researchers in its China lab and some four hundred students who come in and out on projects and become recruiting material for Microsoft. (pp. 266–267)

In contrast, consider the following statements taken from three highly visible scientific outlets published in the United States:

“There is little evidence that those scoring at the very top of the range in standardized tests are likely to have more successful careers in the sciences” (Science, Muller et al., 2005, p. 1043).

“Measures of aptitude for high school and college science have not proved to be predictive of success in later science and engineering careers” (National Academy of Sciences, 2007, p. 2).

“Standardized tests are thus not sufficiently predictive of future performance. Individuals are not necessarily more meritorious if they obtain the highest scores on standardized tests, thus rendering invalid the argument that students with the highest scores should have priority in admissions” (*American Psychologist*, Vasquez & Jones, 2006, p. 138).

The first was signed by 79 scientists and academic administrators from major U.S. universities. To be sure, the political motives that engender statements such as these cannot be dismissed (Benbow & Stanley, 1996; Gottfredson, 2005; Hunt, 1997; Scarr, 1993), but there are other reasons as well. In our culture, and in contrast to athletics, there has been relatively little attention devoted to distinguishing the able from the exceptionally able (Benbow & Stanley, 1996; Colangelo, Assouline, & Gross, 2004; Stanley, 2000). And this has a long history (Achter & Lubinski, 2003; Seashore, 1922). For example, by the time intellectually exceptional performers reach high school, that is, “future PhD level engineers and physical scientists,” essentially all of them are bumping their heads on the ceiling of college entrance exams (Lubinski, Benbow, Shea, Eftekhari-Sanjani, & Halvorson, 2001). These instruments are unable to distinguish those 20 individuals discussed by Friedman (2005). Indeed, it is important to keep in mind that the top 1% of ability consists of over one third of the ability range (e.g., in IQ units, from approximately an IQ of 137 to over 200). Individual differences within this range matter, and they do not cease to operate just because they are not measured. Yet, they are routinely unmeasured. For example, the Graduate Record Exam (GRE), designed for college graduates applying for admission to graduate school is even more insensitive to exceptionalism than the SAT is for college-going high school seniors. On the GRE Quantitative scale, for which scores range from 200 to 800, 30% of the test takers score 700 or more, and only 25% score

under 500 (based on all examinees tested between 1 July 2002 and 30 June 2005).

This instrument is essentially “tone deaf” with respect to identifying truly exceptional talent in quantitative reasoning.

Our research has been devoted, among other things, to the educational implications of individual differences with the top 1% of the ability range. But we go well beyond IQ. Using multiple dimensions of cognitive functioning—quantitative, spatial, and verbal reasoning ability—we seek to uncover the educational implications and contrasting potentialities for growth embodied by different ability levels and patterns. We then try to put this information to applied and theoretical use by suggesting differential educational opportunities for intellectually talented students (Benbow, 1991; Benbow & Stanley, 1996; Stanley, 2000) and evaluating the outcomes. The results are then used to build conceptual frameworks that model educational achievement, occupational accomplishments, and creativity (Lubinski & Benbow, 2000, 2006). For these purposes, our study, the Study of Mathematically Precocious Youth (SMPY), is currently tracking more than 5,000 intellectually talented participants identified over a 25-year period (1972–1997; Lubinski & Benbow, 2006). Some important findings have emerged from this work.

For over 30 years, for example, we have known that 12-year-olds scoring 500 on the SAT mathematics section (SAT-M) or the SAT verbal section (SAT-V) can assimilate a full high school course in 3 weeks at summer residential programs for talented youth; those scoring 700 or more can learn at least twice this amount. More recently, we have learned that these two score differences translate into differential promise for earning a doctorate (i.e., PhD, MD, or JD). The base rate for earning a doctorate in the United States is 1% (i.e., 1% of the U.S. population has a doctorate). Intellectually talented youth scoring 500 or more on one of the SAT scales earn doctorates at 30 times base rate expectations, whereas those scoring 700 or more earn doctorates at over 50 times (30% versus 50%). Moreover, overall, the latter do so at more prestigious universities (Benbow, Lubinski, Shea, & Eftekhari-Sanjani, 2000; Lubinski, Webb et al., 2001); the more exceptional group is twice as likely to attend a top 10 U.S. university.

In a recent study, 2,409 participants identified with the SAT by age 13 as being in the top 1% of intellectual ability were tracked for 25 years; these early assessments possess predictive validity for criteria well beyond academic learning

rates and securing advanced degrees. These early assessments actually portend the likelihood and nature of creative expression later in life. Specifically, Park, Lubinski, and Benbow (2007) analyzed 25-year longitudinal data from the first three SMPY cohorts. SAT-M and SAT-V scores secured by age 13 were transformed into two relatively independent dimensions ($r = .02$), which were subsequently transformed into z scores: ability level (SAT-M + SAT-V) and ability tilt (SAT-M – SAT-V). The former assesses general ability level, the latter differential ability strength. Positive ability tilt scores characterize strengths in quantitative ability relative to verbal ability, whereas negative scores reflect relatively stronger verbal ability.

Two decades later, their accomplishments were classified into area of achievement: the humanities or STEM (i.e., science, technology, engineering, mathematics) and into four broad achievement level groups (those who had secured terminal bachelor's or master's degrees [[Figure 12.1a](#)], those who had secured doctorates [PhDs; [Figure 12.1b](#)], those who had secured a tenure-track position at a U.S. university [[Figure 12.1c](#)], and those who had secured a patent or authored a noteworthy literary publication [[Figure 12.1d](#)]). STEM degrees included the physical sciences, mathematics, computer science, and engineering. Humanities degrees included art, history, literature, languages, drama, and related fields. (Other fields such as the social sciences, biological sciences, health sciences, architecture, business, and management were not analyzed for the purposes of this study.)

[Figures 12.1a](#) through [12.1d](#) represent the two-dimensional space defined by ability tilt (x axis: SAT-M minus SAT-V) and ability level (y axis: SAT-M plus SAT-V). Within each figure, bivariate means for the humanities and STEM groups were plotted, and ellipses were formed around each using ± 1 standard deviation on each dimension. An additional pair of ellipses was constructed in [Figure 12.1c](#) to distinguish those participants who secured tenure-track positions at top 50 U.S. universities from participants with tenure-track positions at other U.S. universities. Units on each axis represent standard deviation units of the entire sample. Additionally, we plotted more specific criterion groups, such as novelists, nonfiction authors, and those who secured an MD or JD, simply as bivariate means without standard deviation ellipses, for a more complete portrait of the accomplishments of this sample.

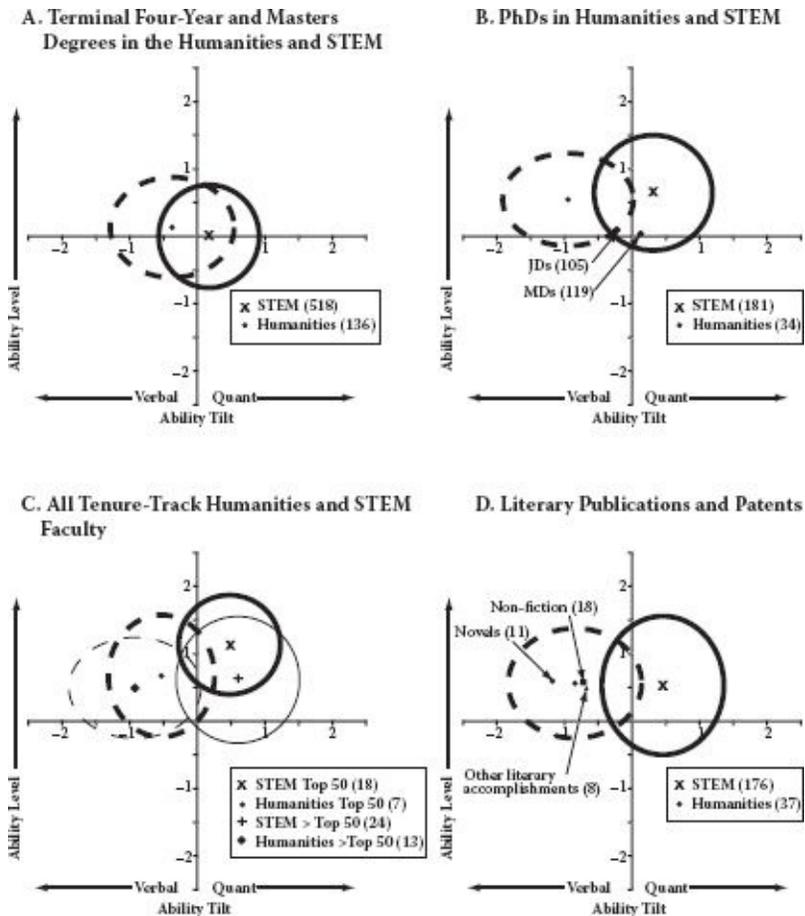


Figure 12.1 Participants' achievements as a function of ability tilt (math SAT score minus verbal SAT score) and ability level (sum of the math and verbal SAT scores), in standard deviation units. The achievement categories examined were (a) completing a terminal 4-year or master's degree, (b) completing a PhD (means for MDs and JDs are also shown), (c) securing a tenure-track faculty position, and (d) publishing a literary work or securing a patent. In each graph, bivariate means are shown for achievements in humanities and in science, technology, engineering, and mathematics (STEM), respectively; the ellipse surrounding each mean indicates the space within 1 standard deviation on each dimension. The mean SAT scores (math, verbal) for the criterion groups were as follows: 4-year and master's STEM degree (575, 450), 4-year and master's humanities degree (551, 497), STEM PhD (642, 499), humanities PhD (553, 572), tenure-track STEM position in a top-50 university (697, 534), tenure-track humanities position in a top-50 university (591, 557), tenure-track STEM position in a non-top-50 university (659, 478), tenure-track humanities position in a non-top-50 university (550, 566), patents–STEM (626, 471), and publications–humanities (561, 567).

Examination of these four panels confirms that the humanities and STEM groups occupy different regions in the space defined by these dimensions. Like most powerful findings, they are readily seen by the naked eye. What is especially clear across all four panels is the importance of ability tilt for STEM versus humanities; participants in the former have quantitatively tilted ability profiles, whereas the latter have verbally tilted profiles. However, for noteworthy

creative achievements, such as securing a tenure-track position, earning a patent, or writing a novel, ability level matters as well. Ability level forecasts the likelihood of creativity whereas ability pattern refines predictions in regard to the domain in which it is likely to occur. To give readers a feel for level of ability in modern SAT units, a z score of zero on the y axis constitutes an SAT composite of approximately 1100 and a z score of one is around 1300 (again, attained before age 13).

For [Figure 12.1c](#), the top 50 U.S. universities are separated from the remainder. It is interesting to note how the ellipses for the top schools converge. This is due to a number of participants earning top possible scores on SAT-M. For example, of the 18 participants who later earned tenure-track positions in STEM fields at top 50 U.S. universities, their mean SAT-M score was 697, and the lowest score among them was 580 (a score greater than over 60% of all participants). Two individuals earned 800, the top possible SAT-M score, which illustrates that for profoundly gifted participants, college entrance exams such as the SAT can manifest ceiling effects even as early as age 12 (cf. Benbow & Stanley, 1996; Muratori et al., 2006; Stanley, 2000). To give further nuance to the accomplishments of this group, 7.3% (176 of 2,409) of this sample earned at least one patent (the base rate for holders of patents in the United States is approximately 1%, of the U.S. population; J. C. Huber, personal communication, October 2004; Huber, 1998, 1999), and their total number of patents was 817. Participants also published 93 books (56 novels, 37 nonfiction books). At age 31, one participant was awarded the Fields Medal (thought of as the Nobel Prize for mathematics), and another participant won the John Bates Clark Medal (most outstanding economist under 40).

That a 3-hour assessment conducted by age 13 captures individual differences that forecast rare accomplishments and qualitatively different developmental trajectories is important for many reasons. Yet, the recent statements in the highly visible outlets quoted earlier assert that there is little evidence that high scores on standardized instruments, such as the SAT, relate to real-world success later in life, particularly in science and technology careers. Our results, and findings that were available well before the comments were published (see Benbow, 1992; Benbow et al., 2000; Benbow & Stanley, 1996; Colangelo et al., 2004; Lubinski, Benbow, et al., 2001; Lubinski, Webb, et al., 2001; Stanley, 2000),

certainly suggest otherwise (for a more comprehensive review, see Lubinski & Benbow, 2006).

Exceptionally high scores on standardized measures of cognitive abilities are informative and highly significant psychologically. Moreover, the individual differences uncovered by administering college entrance exams to 12-year-olds are suppressed by high school or age-17 SAT assessments. When intellectually talented students reach this stage of development, essentially all of their scores cluster near the ceiling or among the top possible scores—the exceptionally able are no longer readily distinguished from the able. Comments from first-rate engineering and physical science faculty like “the SAT-M doesn’t mean much,” because all of their applicants score in the top 700s, are all too familiar. (Our study of graduate students in top STEM programs revealed the reality of such statements; see Lubinski, Benbow et al., 2001). When artificial ceilings are imposed on psychometric measures (like physical measures), variation is constrained and, therefore, the covariation between such measures and meaningful criteria is severely limited.

To adequately reveal the psychological significance of individual differences within the top 1% of ability (over one third the ability range), and for the assessment tools that measure these individual differences to be validated empirically, the following methodological requirements are needed: large samples, measures with high ceilings, criteria with high ceilings or low base rates, and an appreciable time interval for creative achievements to develop. With these design features in place, appraising differential capabilities among intellectually talented populations becomes possible, and the creative promise that these individual differences reflect is revealed. With this, building meaningful models of exceptional human capital now becomes possible. Just as an instrument’s validity is contingent upon its purpose, an instrument’s reliability and validity vary across contrasting stages of development.

MODELING THE DEVELOPMENT OF EXCEPTIONAL HUMAN CAPITAL MORE COMPREHENSIVELY

Abilities are only one class of variables needed for modeling educational, occupational, and creative accomplishments over the lifespan; preferences are another. Interests, needs, and values are the dimensions of human individuality that capture these concepts (Dawis, 1991, 2001; Schmidt, Lubinski, & Benbow, 1998). [Figure 12.2](#) contains the model we have used to conceptualize the identification of different “types” of intellectually precocious youth and to model their development: the theory of work adjustment (TWA; Dawis & Lofquist, 1984; Lofquist & Dawis, 1991). This framework reaches back to form historical connections with Parsons’ (1909) three-step approach to applied psychology, wherein he emphasized an understanding of one’s individuality, knowledge of what the work (or learning) environment required, and honest reasoning between these two sets of information. TWA was developed within counseling psychology (Dawis, 2005), but was generalized to industrial psychology by Katzell (1994), and earlier, we extended TWA’s underlying logic to talent development in educational contexts for intellectually precocious youth (Lubinski & Benbow, 1992; Lubinski & Humphreys, 1990). TWA is a psychological approach predicated on a person–environment fit (Rounds & Tracey, 1990). Given the complexity of the development of talent, TWA was drawn upon to help inform practice, organize empirical findings, and structure our applied and longitudinal research (Lubinski & Benbow, 2000, 2006).

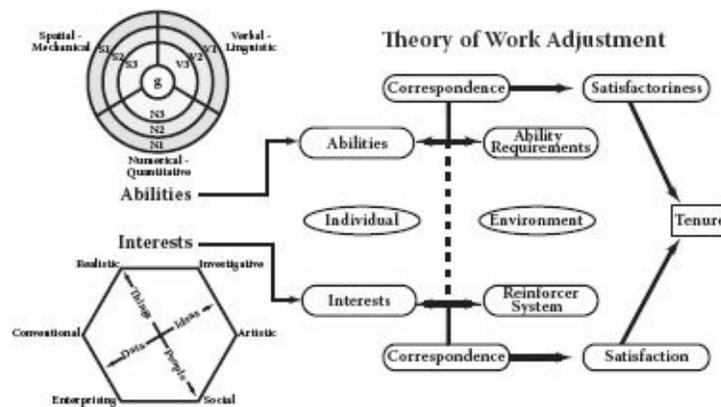


Figure 12.2 The theory of work adjustment (right side) alongside the radex of cognitive abilities (top left)

and RIASEC hexagonal pattern of interests (bottom left), used in combination to understand personal antecedents important to education and vocation (Lubinski & Benbow, 2000). The letters inside the radex pertain to a specific ability, whereas the numbers rise with sophistication. The two lines inside the hexagon are two reduced dimensions (Prediger, 1982), data/ideas and people/things that are central to the RIASEC. The dotted line in the individual and environment sections of TWA delineates the equivalence put on assessing personal attributes (abilities and interests) and environmental attributes (abilities requirements and reward architecture).

From our point of view, educational, counseling, and industrial psychology are each applied disciplines predicated on the scientific study of interventions or opportunities, based on individual differences, for enhancing positive psychological growth in learning and work settings (each developed from a somewhat different focus: school, the transition from school to work, and the world of work). TWA organizes variables that cut across these three stages of life, and places equal emphasis on assessing the environment and the individual throughout the lifespan. We now turn to the two major classes of TWA person–environment variables illustrated in [Figure 12.2](#).

In TWA the environment is viewed from two perspectives: its ability requirements and its reward system. When connected to an individual’s abilities and preferences, two dimensions of correspondence can emerge: *satisfactoriness* and *satisfaction*. Satisfactoriness refers to the alignment between abilities of the individual and the ability requirements of the environment, whereas satisfaction is the correspondence between personal preferences and congruence with the reward structure of the environment. TWA stresses the teaming of abilities and interests, as do others (Gottfredson, 2003; Strong, 1943; Super, 1949; Tyler, 1974; Williamson, 1965), and the match between the person and the environment. When satisfactoriness and satisfaction are both in place, the predicted outcome is tenure (when the person and environment are mutually satisfied with one another, contribute to each other’s growth, and are both motivated to maintain contact or an extended relationship). The latter occurs in a school setting when intellectually talented students are placed in environments with their intellectual peers, and positive social and emotional growth co-occurs with their educational development. Students who are learning at the same rate enable teachers to present the curriculum at an appropriate pace for optimal learning for all students (Benbow et al., 2000; Benbow & Stanley, 1996; Muratori et al., 2006), and talented students do notice and find it frustrating when the pace of the curriculum slows down to a nonoptimal rate (Bleske-Rechek, Lubinski, & Benbow, 2004). If

students share passion, the effectiveness of the learning environment is even further advanced. Students and their environment are in a symbiotic relationship and systematically involved in meeting each other's needs.

To determine whether preferences complement cognitive abilities in forecasting developmental trends among intellectually precocious youth, a series of three discriminant function analyses were conducted. First, Achter, Lubinski, Benbow, and Eftekhari-Sanjani (1999) analyzed data from 432 intellectually precocious youths who had been measured by both the SAT and the Allport, Vernon, and Lindzey (1970) Study of Values (SOV), and who attained a college degree 10 years after their initial assessment (at age 23). Participants were grouped into three categories: humanities, math–science, and other.

Using the SAT-M, SAT-V, and five SOV themes (Theoretical, Aesthetic, Social, Religious, and Economic; Political was excluded arbitrarily due to the ipsative nature of the scale) to determine the score pattern, it was concluded that differential score patterns separated the three groups. [Table 12.1](#) is the discriminant function structure matrix showing the two functions (one per column) and their respective weights. The first function (F_1) characterized a math–science combination of weights, with positive weights for the SAT-M and SOV-Theoretical, and negative weights for Social and Religious values. Whereas, the second function (F_2) characterized a humanities weight combination, with high SAT-V scores and Aesthetic values. Incremental validity of preferences beyond abilities was demonstrated as the SAT-M, and SAT-V accounted for 10% of the variance between the three groups, and the five SOV dimensions accounted for an additional 13%, for a total of 23% of the variance accounted for (which is impressive considering the 10-year gap and the diversity within each of the three broad degree groupings).

Figure 12.1 Discriminant Function Structure Matrix

Variable	F₁	F₂
SAT-Verbal	0.09	0.56
SAT-Math	0.59	-0.12
SOV-Theoretical	0.87	-0.03
SOV-Aesthetic	-0.13	0.81
SOV-Social	-0.60	-0.01
SOV-Religious	-0.56	0.03

Note: The bivariate group centroids for the 10-year data using college degree were (Function 1, followed by Function 2): humanities (-.29, .60); math-science (.43, -.05); other (-.57, -.21). For the age 33 data examining occupations, the group centroids were (F₁, F₂): humanities (-.80, .59), math-science (.80, -.21), and other (-.60, .04). F₁ = Function 1, F₂ = Function 2, SAT = Scholastic Assessment Test, and SOV = Study of Values. From Achter et al. (1999, p. 783).

The visual complement to the discriminant functions in [Table 12.1](#) is given in [Figure 12.3](#), which includes the bivariate means on these functions plotted in this space for the three educational degree groups (math-science, humanities, and other). The data from Achter et al. (1999) is represented by the unshaded triangle in [Figure 12.3](#), and dotted lines drawn from each group's bivariate mean through the midpoint of the other two create mutually exclusive and exhaustive categories specifically indicative of the three educational groupings utilized by Achter et al. In a study by Wai, Lubinski, and Benbow (2005), an analysis similar to Achter et al. was conducted, but this time using occupational group membership (20 years later at age 33) as the criteria for prediction. The logic of this analysis was that if age-13 SAT and SOV assessments could predict occupational attainment at age 33 utilizing functions derived from age-23 educational criteria, this would constitute a successful generalization probe from educational-learning to occupational-work environments, and the two functions in [Table 12.1](#) would accrue additional validity. And indeed they did.

Wai et al. (2005) tracked 511 participants, over 20 years, who had relevant data for the analysis, and again occupations were put into the same three broad groupings (Math-Science, Humanities, and Other), and the scores based on the Achter et al. (1999) discriminant functions were plotted in the same space as Achter et al. ([Figure 12.3](#)). The bivariate means of the occupational data for each group are represented by the shaded triangle. More circumscribed bivariate means for various occupational groupings were also placed in this two-function space (with sample sizes in parentheses), and the proportion of hits and misses for each broad grouping is given for each segment. Beyond the majority of each group falling into the predicted category (a convergent pattern), if a bivariate point is located in the math-science space it is likely the individual is not employed in a humanities occupation, and vice versa (a discriminant pattern). This convergent-discriminant pattern captures empirically what C. P. Snow (1998) described as the two cultures, where the term *culture* is precisely meant in

both meanings: “development of the mind” (1998, p. 62) and “a group of persons living in the same environment, linked by common habits, common assumptions, a common way of life” (1998, p. 64). Or, following Scarr (1996; Scarr & McCartney, 1983) the pattern reflects the person–environment features of a congenial psychological niche.

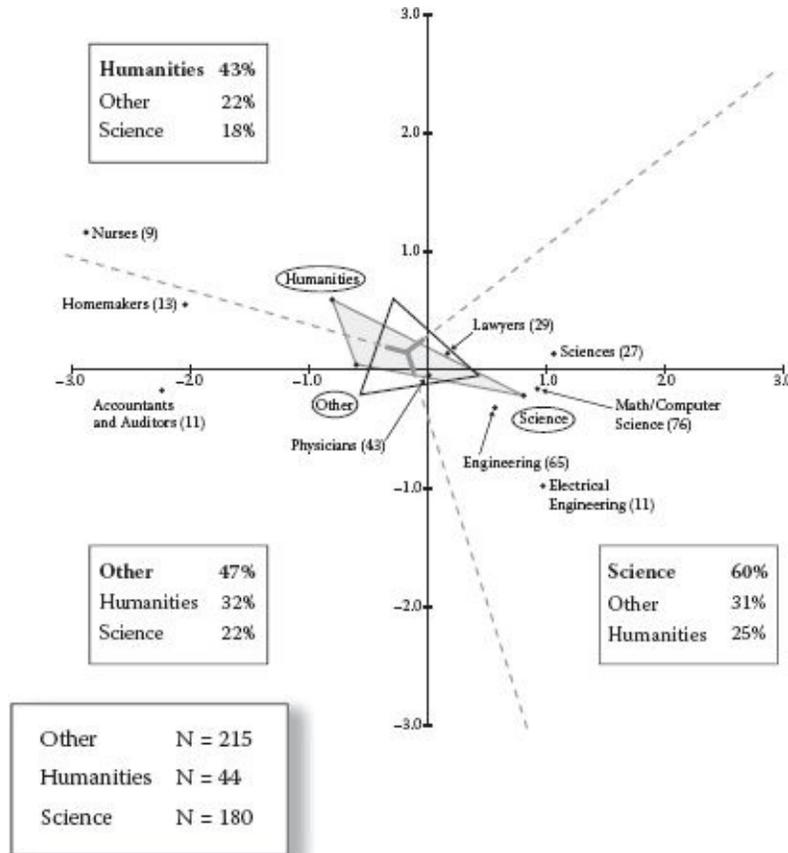


Figure 12.3 Bivariate group centroids (means) for occupations. The unshaded triangle is created by F_1 and F_2 group means for college majors at age 23, whereas the shaded triangle is defined by F_1 and F_2 group means for occupational groups at age 33. The group centroids for the data collected at age 33 were (F_1 , F_2) humanities (-.80, .59), math–science (.80, -.21), and other (-.60, .04). Science = math–science occupations; F_1 = Function 1; F_2 = Function 2. Percentages were computed utilizing individual data points. Physicians, lawyers, and other occupations are placed in this space with sample sizes in parentheses. Taken from Wai et al. 2005.

Also, interesting to note in [Figure 12.3](#) is a people versus things (or organic versus inorganic) dimension that can be traced from slightly above the negative x axis (around homemakers and nurses), through the origin, to slightly under the positive x axis (near engineers and computer scientists). Based on both the Achter et al. (1999) and Wai et al. (2005) studies, there is no question that in the

prediction of educational and occupational choice, both abilities and preferences contribute unique information relative to each other. These functions isolate environments where people are likely to be most comfortable and have the most potential for developing expertise and personal fulfillment.

Although the studies reviewed so far in this section have included mathematical and verbal reasoning abilities, the radex of cognitive abilities ([Figure 12.2](#)) also includes spatial ability (Snow & Lohman, 1989). A recent study by Webb et al. (2007) utilized all three specific abilities along with both the RIASEC + Abilities and the SOV + Abilities to forecast learning and work criteria at age 18. RIASEC is based on Holland’s (1996) hexagon of vocational interests (realistic, investigative, artistic, social, enterprising, and conventional), which parallels the SOV in many respects, and is the most widely used model in vocational psychology (Rounds & Day, 1999). In this 5-year longitudinal study, five criterion variables were examined: (1) favorite and (2) least favorite high school course, (3) leisure activities, (4) college major, and (5) intended occupation. Results are too involved to review systematically here. But in summary, spatial ability was demonstrated to hold incremental validity for these predicted variables beyond the SAT combined with either the RIASEC or SOV. In parallel to the Achter et al. (1999) and Wai et al. (2005) first discriminant functions, the Webb et al., function one (F_1), for both SOV + Abilities and RIASEC + Abilities, a noticeable math–science pattern was uncovered; for each set of analyses, [Table 12.2](#) contains the average variable weights across all five criteria. That is, for math–science there were positive weights for mathematical and spatial ability, negative ones for verbal ability, linked with positive theoretical and negative social, aesthetic, and religious preference loadings.

Table 12.2 Two Sets of first Discriminant Functions (F_1), One Set Involving the SOV the Other RIASEC, for Predicting Three Criterion Groups: math–science, Humanities, and Other

Values + Abilities	F_1	Interests + Abilities	F_1
Theoretical	.57	Realistic	.11
Aesthetic	-.42	Investigative	-.04
Social	-.36	Artistic	-.69
Economic	.47	Social	-.51
Religious	-.17	Enterprising	-.42
SAT-V	-.19	Conventional	.02

SAT-M	.39	SAT-V	-.24
Spatial ability	.70	SAT-M	.30
		Spatial ability	.64

Note: Numbers reflect the average weights of two first discriminant functions (F_1), based on three abilities (verbal + math + space) and either the SOV or the RIASEC (reflecting values and interests, respectively) in predicting three criterion groups (humanities, math–science, and other). SAT-V = SAT-Verbal or verbal ability; SAT-M = SAT-Mathematics or math ability. Adapted from Webb et al., 2007.

Although these results were derived from a 5-year study examining primarily intentions and not actual outcomes, the pattern found here has already been discovered in more mature groups (Austin & Hanisch, 1990; Gohm, Humphreys, & Yao, 1998; Humphreys, Lubinski, & Yao, 1993), suggesting that these findings hold reasonable promise, especially when placed alongside the words of Snow (1999, p. 136): “There is good evidence that [visual-spatial reasoning] relates to specialized achievements in fields such as architecture, dentistry, engineering, and medicine ... Given this plus the longstanding anecdotal evidence on the role of visualization in scientific discovery, ... it is incredible that there has been so little programmatic research on admissions testing in this domain.” We would add that this is especially needed, given the range of individual differences in spatial ability as well as other parameters of cognitive functioning within the top 1% of ability. For all three cognitive abilities examined here, the top 1% contains over one third the range. Therefore, a comprehensive mapping of human learning and work potential is incomplete without cognitive ability profiles that include mathematical, verbal, *and* spatial abilities based on assessments capable of revealing their full scope (Lubinski & Benbow, 2000, 2006), and the same is true for modern talent searches seeking to identify different “types” of intellectually precocious youth (Shea, Lubinski, & Benbow, 2001; Webb, Lubinski, & Benbow 2007).

Our understanding of cognitive abilities, preferences, and other relevant human attributes should be reflected in practice; otherwise, providing optimal environments for intellectually precocious youth will necessarily be less than they could otherwise be (Benbow & Stanley, 1996; Colangelo et al., 2004). The Webb et al. (2007) study is currently the most complete step toward establishing the verisimilitude of applying TWA—and attendant assessment tools designed for older students—to intellectually precocious youth. The latter are not a categorical type, and understanding their psychology of learning and work requires a

multidimensional approach (Dawis, 1992; Scarr, 1996).

COMMITMENT

Our model of talent development as outlined so far is useful for gaining a purchase on how choices are made, and the learning and work performance that ensues after choice. Just like learning prepares students for more complex material, developmental choices result in more complex choices for development. As we age, some life pressures drop out while others come into play, which impacts choice in a recursive manner (Ferriman, Lubinski, & Benbow, in press). Yet, of all the choices for understanding life span development, and especially exceptional development encompassing expertise and world-class performances (Ericsson, 1996; Eysenck, 1995; Gardner, 1993; Simonton, 1988, 1994), how one chooses to allocate time is a most critical consideration. Though not discussed so far in this chapter, this is likely the most agreed upon finding in the talent development literature. And it has stimulated truisms like, “The harder I work, the luckier I am,” “Luck favors the prepared mind,” and “Genius is 2% inspiration 98% perspiration.”

Thus, what is important to keep in mind is that even among individuals with the same TWA ability/preference structure, there are huge individual differences in other personal attributes, such as hours worked and hours willing to work, that differentiate otherwise highly similar learning and work personalities (see [Figures 12.4](#) and [12.5](#)). Persistence and focused time on tasks are among the most important determinants of success, but are frequently neglected in treatments of human capital by those outside the talent development area. In free societies, pursuing excellence is for the most part a choice, a choice that involves time investment beyond the norm and compromises in other domains (Lubinski & Benbow, 2001). Thus, even among those with exceptional potential, only a small fraction choose to invest the amount of concentrated effort required to develop the level of expertise needed to push intellectually demanding domains forward.

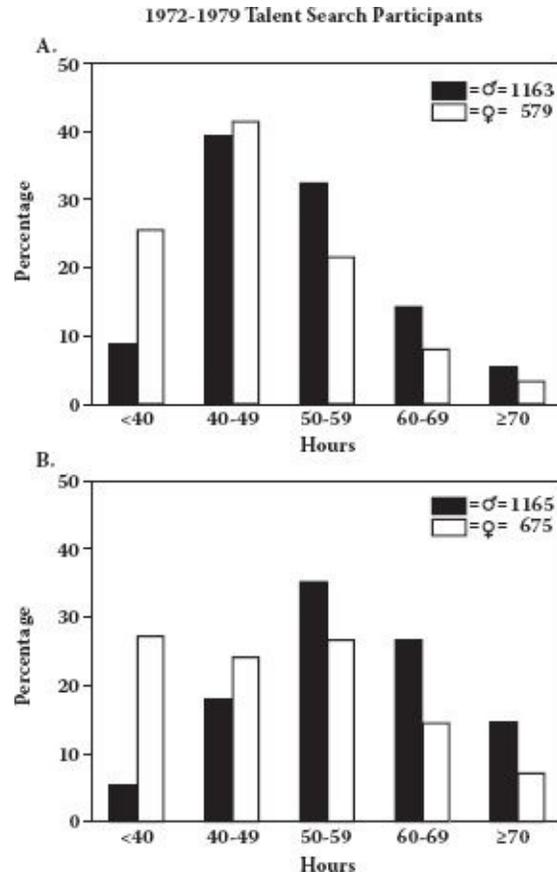


Figure 12.4 Two questions about work taken from SMPY's 20-year follow-up questionnaire (adapted from Lubinski & Benbow, 2000). Participants were identified at age 13 as having quantitative reasoning abilities within the top 1% of their age group. At age 33, they were asked (top panel) how many hours per week they typically worked (excluding homemakers), and (bottom panel) how many hours per week they were willing to work, given their job of first choice.

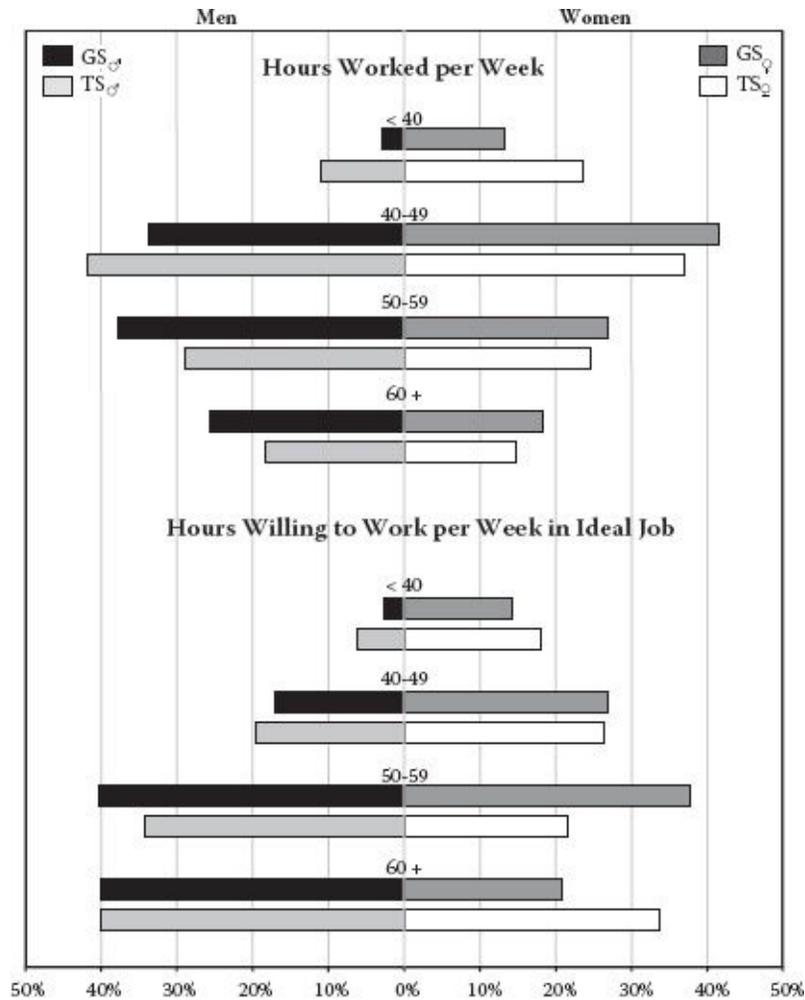


Figure 12.5 Hours worked and hours willing to work per week in ideal job for top U.S. graduate students (GS) and top 1 in 10,000 talent search (TS) participants paralleling Figure 12.4. Total sample numbers for hours worked were 276 male GS, 264 female GS, 217 male TS, and 54 female TS participants. Total sample numbers for hours willing to work were 269 male GS, 263 female GS, 206 male TS, and 57 female TS participants. From Lubinski et al. 2006.

The personal cost may be perceived as too high, seeing it as a choice between “working to live” and “living to work.” True eminence seems to require the latter. This is one reason why the manifestation of creativity is so rare.

CONCLUSION

Sandra Scarr's work has stressed the importance of taking the multidimensionality of human individuality into account when modeling lifespan development and the differential paths people choose. We have tried to extend her views to conceptualizing extraordinary forms of talent development. The great counseling psychologist Leona E. Tyler (1974, 1992) stressed the importance of taking into account the stable features of one's individuality before making life decisions (choices about different possibilities in life) when unpredictable events guaranteed by the vicissitudes of life are encountered. Scarr (1992, 1996; Scarr & McCartney, 1983) has stressed the same for building scientific models of differential development. By not doing the former, we are unlikely to make good personal choices; by not doing the latter, our models are guaranteed to be incomplete. What we would stress here is the importance of assessing the full range of human psychological diversity, because it is so often underappreciated. When it comes to conceptualizing extraordinary human accomplishments, model building in developmental psychology has been constrained by measures that do not capture the full scope of human potential. When developmentally appropriate measures are utilized in a manner suggested in this chapter, the scientific yield that accrues over protracted intervals has the potential to impress Sandra Scarr herself.

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