

Who Shines Most Among the Brightest?: A 25-Year Longitudinal Study of Elite STEM Graduate Students

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In 1992, the Study of Mathematically Precocious Youth (SMPY) surveyed 714 first- and second-year graduate students (48.5% female) attending U.S. universities ranked in the top-15 by science, technology, engineering, and mathematics (STEM) field. This study investigated whether individual differences assessed early in their graduate school career were associated with becoming a STEM leader 25 years later (e.g., STEM full professors at research-intensive universities, STEM CEOs, and STEM leaders in government) versus not becoming a STEM leader. We also studied whether there were any important gender differences in relation to STEM leadership. For both men and women, small to medium effect size differences in interests, values, and personality distinguished STEM leaders from nonleaders. Lifestyle and work preferences also distinguished STEM leaders who were more exclusively career-focused and preferred to work—and did work—more hours than nonleaders. Also, there were small to large gender differences in abilities, interests, and lifestyle preferences. Men had more intense interests in STEM and were more career-focused. Women had more diverse educational and occupational interests, and they were more interested in activities outside of work. Early in graduate school, therefore, there are signs that predict who will become a STEM leader—even among elite STEM graduate students. Given the many ways in which STEM leadership can be achieved, the gender differences uncovered within this high-potential sample suggest that men and women are likely to assign different priorities to these opportunities.

Keywords: STEM leaders, eminence, talent development, individual differences, intelligence

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Innovations from occupations in science, technology, engineering, and mathematics (STEM) fuel the engines of modern economies. In 2013, the United States spent \$456.1 billion—2.7% of the gross domestic product (GDP)—on STEM research and development (National Science Board, 2016). However, the truly extraordinary advances in STEM have not been the work of typical individuals in the STEM workforce. Rather, rare, talented, and committed individuals within STEM have produced such advances. They developed cutting-edge expertise over lengthy inter-

vals of intense training and continuously sharpen and update these skills for years following their formal education (Isaacson, 2011; Murray, 2003; Roe, 1961, 1965; Simonton, 2014; Zuckerman, 1977). Their commitment, knowledge, and passion distinguish them from their peers. Even among STEM graduate students trained at the best universities in the world, only a small subset become STEM leaders. What are their notable psychological characteristics? What distinguishes them from their graduate student peers? How early in their development are these differences apparent? Do the same attributes distinguish men and women who become STEM leaders? This study empirically answers these questions (Ceci, Ginther, Kahn, & Williams, 2014; Ceci & Williams, 2011; Eysenck, 1995; Simonton, 2014; Zuckerman, 1977).

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Theoretical Orientation

This longitudinal study of STEM eminence utilizes psychological frameworks that stress the importance of aligning abilities, interests, and personality dimensions in building models of “promise” for contrasting educational and occupational pursuits. They include “trait complexes” in education (Corno et al., 2002; Snow, Corno, & Jackson, 1996) and “taxons” in the world of work (Dawis & Lofquist, 1984; Lofquist & Dawis, 1991). In his model of intellectual development, Ackerman (1996; Ackerman & Heggstad, 1997; von Stumm & Ackerman, 2013) labeled such constellations “trait clusters.” Other theorists have assembled combinations of abilities, interests, and personality to reveal the role

that they play in the development of identity and social roles more generally (Gottfredson, 1981, 2002, 2005; Roberts & Wood, 2006).

These models seek to explain individual differences in educational and occupational choices, as well as individual differences in performance after choice. The *level* and the *pattern* of abilities, interests, and personality organized within these frameworks shape important life choices. For example, individuals with high mathematical ability, spatial ability, and scientific interests are likely to pursue STEM careers (Austin & Hanisch, 1990; Gohm, Humphreys, & Yao, 1998; Gottfredson, 2003; Humphreys, Lubinski, & Yao, 1993; Smith, 1964; Super & Bachrach, 1957; Wai, Lubinski, & Benbow, 2009). These individual differences drive the acquisition of different kinds of knowledge and expertise (Ackerman & Lakin, 2018), which in turn shape individual differences in the breadth and depth of the skills attained.

All these frameworks—in particular, the Theory of Work Adjustment (TWA; Dawis & Lofquist, 1984)—explicitly state that abilities and interests are the central features that structure each individual's learning and work development. According to TWA, an individual's interests and abilities should fit with the environment. Good person-environment fit is having one's interests match the rewards of the job (e.g., compensation and the type of work) and having one's abilities match the demands of the job (e.g., the skills needed to complete tasks and manage unanticipated events). TWA places equal emphasis on assessing the person and the environment. The degree of fit determines the extent to which individuals and environments embrace and maintain a committed relationship. The value placed on this relationship by the individual is determined by the environment's capacity to meet the individual's needs; the value placed on this relationship by the environment is determined by the individual's capacity to meet the environment's needs. Taken together, this fit maximizes an individual's personal fulfillment and work performance.

TWA has always stressed the importance of conducting intra- and interindividual differences appraisals. While it is important to determine the abilities and interests required for different career paths, it is also important to consider the overall pattern of an individual's profile—particularly if there are any characteristics that stand out among the rest. Although all personal attributes influence development, the prominent features of one's individuality play a central role in the decisions people make and how they perform following the decisions they do make. This point is critical because each individual has abilities for and interests in multiple things. When people are free to choose, they still must make specific choices about their education and career. TWA suggests that individuals make the best personal choices when they include all aspects of who they are and when they maximize the fit to their education and occupation. This approach is optimal for individual decision-making (Dawis, 1992; Lubinski & Benbow, 2000, 2001; Tyler, 1992), as well as for modeling psychological phenomena (Revelle, Wilt, & Condon, 2010; Sackett, Lievens, Van Iddekinge, & Kuncel, 2017; Stoll et al., 2017).

Although individual differences are critical in shaping educational and occupational choices that people make, we recognize that "choice" may imply more personal autonomy and control than is warranted. Even though people may have outstanding abilities for and interest in STEM disciplines, they may have other interests, time constraints, personal limitations, as well as facing struc-

tural, external obstacles that pull them into different educational and career directions. For example, an individual who has a family member or is personally challenged with a chronic illness may make different educational and career choices than an individual free of such concerns. While clearly important, they are beyond the scope of the present study. The current study is limited to the individuality that top STEM graduate students bring to their post-secondary education in the world's leading universities for the development of STEM expertise. To what extent do the personal attributes that they bring with them to graduate school factor into determining those who ultimately achieve eminence in STEM? This is the restricted focus of the current study.

Exceptional Development

Whether in athletics, the arts, music, or any discipline, it is critical for each individual to find the optimal learning and work environment that matches their specific attributes. In the study of eminence, this fit determines the extent to which an individual with exceptional potential finds opportunities to best develop specific expertise; likewise, this fit influences the likelihood that the environment chooses to select these individuals as well as invest time and resources in their development (Dawis & Lofquist, 1984; Lofquist & Dawis, 1991; Lubinski, 2016; Sackett et al., 2017). By definition, excellence is atypical. To distinguish oneself, an individual must stand out in one or more ways from the norm of their reference group (Eysenck, 1995; Murray, 2003; Simonton, 2014; Zuckerman, 1977). Environments conducive to fostering the development of cutting-edge performances are atypical as well. They seek individuals who excel in the attributes required by the discipline, and they impose exceedingly high standards on them. Outstanding individuals excel under such demanding conditions (Friedman, 2005; Zakaria, 2011).

To the extent that "people make the place" (Gottfredson & Richards, 1999; Schneider, 1987), the salient features of individuality found in cutting-edge learning and occupational environments create distinct niches and social climates. The requirements at Caltech or MIT, Carnegie Hall or Julliard School of Music, and major Washington, DC or New York City law firms are far more selective and demanding than the typical educational and work environments populated by engineers, musicians, and lawyers, respectively. Information on both level and pattern are required to characterize the individuality (i.e., human capital) found in typical and atypical environments. Performance requirements and incentives are proportional to performance expectations. In cutting-edge environments, the high levels of commitment, competence, and motivation are palpable (Campbell, 1977; Eysenck, 1995; Gardner, 1993; Roe, 1953; Simonton, 2014; Zuckerman, 1977). Arguably, the most widely agreed on finding in the talent development literature is the inordinate time world-class performers devote to their career (Campbell, 1977; Ericsson et al., 2006; Eysenck, 1995; Gardner, 1993; Jensen, 1996; Murray, 2003; Simonton, 1988, 2014; Wilson, 1998, pp. 55–56; Zuckerman, 1977). It is the product of their inordinate levels of commitment and passion.

For the above reasons, both theoretical considerations and the selection of variables for studying eminence require considering aspects of individuality that operate when people make more general life decisions, especially how they decide to allocate their time. This is especially true at the point of earning one's terminal

degree (Ferriman, Lubinski, & Benbow, 2009; Geary, 2010; Pinker, 2008; Rhoads, 2004). Typically, the conclusion of formal education is an important catalyst for decisions about life and work, guided by personal priorities and contextual factors, among other things. These decisions compound with each other. Important life decisions require factoring in personal agendas, competencies, and preferences outside of one's work activities (Geary, 2010; Goldin, 2014; Hakim, 2000; Pinker, 2008, Rhoads, 2004).

Finding one's best fit in education or occupation is one thing. Finding it in life is another matter because of the multiplicity of personal motives that compete for a finite amount of time. Economic and psychological theorists have studied work preferences and priorities in conjunction with preferences and priorities for outside-of-work activities. Not surprisingly, there are individual differences (Geary, 2010; Goldin, 2014; Hakim, 2011). These considerations take on particular significance in studying eminence because achieving distinction requires securing postformal education opportunities for optimal development and continually maintaining focus (Eysenck, 1995; Murray, 2003; Simonton, 2014; Zuckerman, 1977). When faced with exceptional career opportunities, individuals with outstanding potential make different choices. For some, choosing to live overseas or in a rural versus a metropolitan area involves intense sacrifice. For others, these choices are a minor inconvenience, or even a source of satisfaction. These decisions are the outcomes of both personal priorities and preferences, as well as structural, contextual factors, each with varying weight and importance in the decision-making process. As experienced mentors of future scientists know, such mundane aspects of life can either attenuate the full career development of their advisees or accelerate them forward.

The above considerations illustrate why both work-related individual differences as well as life preferences and priorities are required to model STEM eminence longitudinally. When exceptional graduate students complete their formal education, reliable individual differences in occupational accomplishments unfold exponentially (Ceci et al., 2014; Gino, Wilmoth, & Brooks, 2015; Hakim, 2000, 2011; Lubinski, Benbow, & Kell, 2014). As such, an outstanding group of STEM graduate students, trained in outstanding graduate programs matching their potential, is ideal for the longitudinal study of STEM eminence. They differ from other mathematically talented participants in important ways because more than outstanding mathematical ability is required to become a STEM leader.

Differences Between Elite STEM Graduate Students and Mathematically Precocious Youth

In 1992, the Study of Mathematically Precocious Youth (SMPY) surveyed elite STEM graduate students ($N = 714$; 48.5% female), for longitudinal study. At that time, their Time 1 data were profiled along with a group of their intellectual peers selected solely based on their exceptional mathematical ability (Lubinski, Benbow, Shea, Eftekhari-Sanjani, & Halvorson, 2001). The elite STEM graduate students were attending a top-15 STEM graduate program in the U.S.; the comparison group was identified as mathematically gifted adolescents in the top 1% of ability. The comparison group was selected through talent searches designed to identify intellectually talented youth for advanced learning oppor-

tunities (Benbow & Stanley, 1996; Lubinski & Benbow, 2006), and they were followed-up in their mid-20s. Analyzing the Time 1 data on the STEM graduate students revealed that men and women had more similarities than differences. Across a variety of psychological attributes, they exhibited prototypical profiles of outstanding engineers and physical scientists found in the psychological literature (Eiduson & Beckman, 1973; Lubinski & Benbow, 2006; Roe, 1951, 1961, 1965; Su, Rounds, & Armstrong, 2009; Terman, 1954b, 1955). For example, they displayed: (a) high levels of mathematical reasoning abilities (and an ability profile tilted toward higher mathematical ability relative to verbal ability); (b) dominant scientific interests; (c) prominent theoretical values (with lower religiosity); and (d) mathematics and science as their favorite high school courses. The patterns in their precollege educational histories and preferences were strikingly similar. As graduate students, men and women alike were devoting 50 hr per week to STEM research and study, comparable with the time that tenured and tenure-track faculty devote to their careers (Ceci et al., 2014, p. 108).

However, when these top STEM graduate students were contrasted to the comparison group (top 1% of mathematical ability), some important differences emerged. Male and female STEM graduate students had similar educational histories and psychological profiles relative to gifted men in the comparison group; however, their profiles were quite different relative to gifted women in the comparison group. Mathematically gifted women had a more uniform ability profile (i.e., their mathematical and verbal abilities were on similar levels), balanced interests and values, and their educational histories were characterized by a more evenly distributed selection of courses and favorite courses (i.e., from humanities to sciences). These gifted women were equally impressive academically and intellectually, but they were less STEM-focused. They had broader interests compared with the other three groups, and this pattern characterized their early development and continued through young adulthood.

This analysis was informative in several ways. For the STEM graduate student sample, a group of young women of this caliber had never been comprehensively profiled before. They possessed extraordinary STEM potential, and their educational histories and psychological profiles mirrored those of their male counterparts. In building a cumulative science (Open Science Collaboration, 2015), these findings fit with decades of longitudinal research on the development of elite STEM talent (Eiduson & Beckman, 1973; Humphreys et al., 1993; Roe, 1953, 1961, 1965; Super & Bachrach, 1957; Terman, 1954b; Zuckerman, 1977). For both men and women, their abilities, interests, and values profiles were conspicuous at an early age, and their passion for STEM likely factored into their course selection and educational experiences well before college (Lubinski, Benbow et al., 2001, Tables 2 and 3, pp. 314–315). It was clear that these STEM graduate students were much more than a group of mathematically talented individuals. It also was clear why world-class STEM graduate training programs valued their personal attributes and accomplishments—they form the fabric from which eminence in STEM emerges.

These findings also were instructive in showing that gender differences among mathematically talented participants mirrored robust findings in both normative samples and among intellectually precocious young adolescents. Even though intellectually talented men and women earn similar proportions of advanced de-

grees (Ceci et al., 2014; Geary, 2010; Lubinski, 2016; Lubinski & Benbow, 2006), they choose their advanced degrees in different disciplines (e.g., 80% of developmental psychologists and 75% of students in veterinary medicine are women). In normative and intellectually talented samples, male intellectual profiles are much more “tilted” (i.e., higher mathematical ability relative to verbal ability), whereas females are more balanced (Humphreys et al., 1993; Stoet & Geary, 2015, 2018).¹ There are also approximately one standard deviation differences in three-dimensional spatial visualization (Hedges & Nowell, 1995; Voyer, Voyer, & Bryden, 1995) and in people-versus-things interests (Su et al., 2009). Males also display a larger variance in mathematical reasoning and spatial visualization relative to females (Geary, 2010; Hedges & Nowell, 1995; Wai, Cacchio, Putallaz, & Makel, 2010); therefore, there are more males than there are females at both the lower- and the upper-tail distributional extremes. When this is coupled with well-documented gender differences in preferences for working part-time (Goldin, 2014; Hakim, 2000, 2006; Lubinski & Benbow, 2006; Lubinski et al., 2014; Pinker, 2008; Rhoads, 2004), the determinants of gender differences in STEM careers at the outer edge of the envelope become an anticipated consequence. These differences also contribute to why women are overrepresented in other disciplines.² The female graduate students studied in the present investigation are atypical in that they are psychologically much more removed from the norm of their gender than the males are from theirs.

Current Study

The current study examined these STEM graduate students 25 years after their initial assessment. The first purpose of this study was to determine whether there were individual differences that distinguished graduate students who became STEM leaders from those students who did not become STEM leaders. Although the Time 1 psychological profiles for men and women fit with prior expectations based on several studies of outstanding engineers and physical scientists (Lubinski & Benbow, 2006; Roe, 1951, 1953; Super & Bachrach, 1957; Terman, 1954b; Zuckerman, 1977), large individual differences were observed across all the attributes under analysis. We were curious as to whether these individual differences were predictive of those who ultimately became extraordinary STEM contributors. The second purpose of this study was to determine whether there were gender differences between STEM leaders and nonleaders (i.e., graduate students who had less remarkable STEM careers or who pursued careers outside of STEM). We also were curious whether the same personal attributes and experiences operated uniformly for women and men in the development of truly outstanding STEM careers.

Method

Participants and Procedure

In 1992, 714 first- and second-year graduate students (mean age = 24.5 years, $SD = 1.9$ years) enrolled in doctoral programs from the top-15 universities in the U.S. by various STEM disciplines were recruited to participate in this study (Lubinski, Benbow et al., 2001). There was an emphasis to survey students from

inorganic disciplines, although two disciplines with an organic component were included (biochemistry and bioengineering). Women were oversampled to achieve proportional representation within each discipline and department (368 males, 346 females). All participants were U.S. citizens because the initial focus was on U.S. approaches to education and talent development. Each graduate program was instructed to enlist all first- and second-year female graduate students who wished to participate. Then, each graduate program randomly sampled the same number of first- and second-year male graduate students from the same program. All participants received \$15 for participating in this study.

In 2002, data collected in their 10-year follow-up (at age 35) were analyzed in two subsequent studies (Ferriman et al., 2009; Lubinski, Benbow, Webb, & Bleske-Rechek, 2006). The current study’s assessment of STEM leadership draws on data from objective and publicly available records of STEM accomplishments when they were Age 50 (see below). We evaluated their STEM leadership status in 2016–2017, 25 years after their initial identification. The Institutional Review Board (IRB) approved this study (Vanderbilt University, #020469, “SMPY: Cohort 5”).

Assessment Design

At Time 1, each participant completed a biographical survey; in addition, they provided copies of their College Board Graduate Record Examination (GRE) score report and their undergraduate transcript (Lubinski, Benbow et al., 2001). To enhance the construct validity of our measurement protocol, we collected assessments from multiple data sources following Cattell’s (1957) recommendations: L-data (life record), T-data (tests or objective assessments), and Q-data (questionnaires). These assessments in-

¹ These considerations are related to large scale and cross-cultural meta-analyses, which document how contextual determinants and external barriers interact with one’s individuality at both the individual and group level. For example, cross-cultural studies found that societies that are more egalitarian, gender disparities in STEM become more pronounced (Stoet & Geary, 2015, 2018). These findings suggest that egalitarian societies allow people the freedom to respond to their individuality (i.e., their unique profile of abilities, interests, and personality). Like men and women in general (Gottfredson, 2003; Geary, 2010), mathematically talented women are more likely than mathematically talented men to have uniform math/verbal ability profiles, and they are more oriented toward organic and social subject matter (Achter et al., 1996; Lubinski & Benbow, 2006; Lubinski et al., 2014; Su et al., 2009). According to TWA, these differences suggest that men and women prefer to develop their talents somewhat differently (as they experience more freedom and autonomy to choose); however, these differences would not be expected to influence the level of their accomplishment. Nevertheless, it is important to stress that the study of human individuality consistently finds that the magnitude of group differences is modest compared to the individual differences within groups. Therefore, for optimal talent development interventions and opportunities, it is always best to treat each person as an individual rather than as a member of some group (Benbow & Stanley, 1996; Corno, Cronbach, et al., 2002; Gottfredson, 2003; Lubinski, 1996, 2010); this entails tailoring interventions and opportunities in accordance with their individuality.

² Yet, these differences do not mean there are gender differences in other outcomes. For example, a recent longitudinal study of mathematically talented adolescents revealed that males and females at midlife were highly and uniformly satisfied by their differential educational and occupational choices (Lubinski et al., 2014), and other valued aspects of their lives.

cluded ipsative and normative questionnaires, as well as biographical items for both qualitative and quantitative appraisals. This enabled us to employ a mixed-methods data analytic approach.

Age 25: Assessment Instruments

Ability. Participants provided copies of their GRE report. We ran analyses on their verbal (GRE-V), quantitative (GRE-Q), and analytical (GRE-A) scores. Composite scores from these three tests were calculated to assess general intellectual ability (Frey & Detterman, 2004; Lubinski, 2004).

Educational history. Our biographical questionnaire included questions on participants' educational history and experiences from elementary school through their undergraduate education (Lubinski, Benbow et al., 2001). These questions included whether they participated in gifted programs, advanced placement (AP) courses, grade skipping, and other educational experiences beyond the norm. Participants also reported whether they received any special awards or honors (e.g., National Merit finalists and scholars, Presidential Scholars, honor society members).

Interests. We assessed educational-vocational interests with the Strong Interest Inventory (SII; Hansen & Campbell, 1985). This instrument included both broad and specific interest scales. The broad scales were the six general occupational themes, commonly known as Holland's (1959, 1999) Hexagon or the RIASEC dimensions. RIASEC themes are organized hexagonally; adjacent themes are more highly associated with each other while opposite themes within the hexagon are least related. Therefore, the covariance between each of the six themes is inversely proportional to the distance between them, a property referred to as "Holland's calculus." Empirical research has consistently replicated this hexagonal structure (Day & Rounds, 1998; Hoff, Briley, Wee, & Rounds, 2018; Savickas & Gottfredson, 1999). Briefly, the six RIASEC themes can be described as: realistic (enjoys working with things, especially in the outdoors, a need for structured environments); investigative (interests in science and mathematics, working independently); artistic (interests in art, writing, creative expression, does not like operating in highly structured environments); social (interests in the helping professions and working with people); enterprising (seeks leadership roles, especially for accomplishing economic goals); and conventional (prefers working in structured environments and a well-defined chain of command, more of a follower than a leader).

RIASEC is the most widely used general model of educational-occupational interests today (Day & Rounds, 1998; Hoff et al., 2018); and the SII is the premier instrument for assessing educational and occupational interests. However, the SII also contains 23 Basic Interests Scales (BIS). While the RIASEC themes are more widely known and employed in research, compelling data suggest that more specific interest measures, such as the BIS, increase the accuracy of specific predictions about career development (Liao, Armstrong, & Rounds, 2008; Ralston, Borgen, Rottinghaus, & Donnay, 2004; Su et al., 2009).

The BIS are facets of the broader RIASEC themes, based on extensive factor analytic and applied research (Campbell, 1971; Campbell & Borgen, 1999; Campbell, Borgen, Eastes, Johansson, & Peterson, 1968). It is worth mentioning that occupational researchers have often bemoaned the underutilization of the BIS, given their incremental validity. Their limited use is likely due to

time constraints, a common issue in assessing individual differences comprehensively. The BIS provide a more nuanced view of specific interests of our participants. Precisely how the RIASEC dimensions are expressed is shaped by their facets. These facets (preceded by the RIASEC letter with which they are associated) are: *realistic* (agriculture, nature, adventure, military activities, and mechanical activities); *investigative* (science, mathematics, medical science, and medical service); *artistic* (music, art, and writing); *social* (teaching, social service, religious activities, domestic arts, and athletics); *enterprising* (public speaking, law/politics, merchandise, sales, and business management); and *conventional* (office practices).

Values. The Study of Values (SOV; Allport, Vernon, & Lindzey, 1970) is an ipsative measure that assesses the relative prominence of six values according to Spranger's (1928) personality-related types: theoretical (values discovery of truth, and focuses interests on empirical, critical, and rational thought); economic (values pragmatism and being practical, views unapplied knowledge as wasteful); political (values personal influence, desires power and notoriety); aesthetic (values form and harmony and is interested in the aesthetic side of life); social (values altruistic and philanthropic love of others, and is unselfish and sympathetic); and religious (values unity, and tries to comprehend the cosmos and relate it to the self). Scores on the six values sum to 240 (with each value having a normative mean of 40), and scales provide an intraindividual appraisal of participants' value orientation and approach to life (Dawis, 1991).

Just following the SOV's 1970 revision, it was the third most frequently cited nonprojective personality test in use. However, its use has declined over the past three decades, largely due to the dated and noninclusive language in some items. We addressed this issue by slightly updating the language in a few questions, which did not attenuate the SOV's reliability or concurrent and predictive validity (Achter, Lubinski, & Benbow, 1996; Achter, Lubinski, Benbow, & Eftekhari-Sanjani, 1999; Lubinski, Schmidt, & Benbow, 1996; Schmidt, Lubinski, & Benbow, 1998). More recently, Kopelman, Rovenpor, and Guan (2003) modernized the SOV in a further revision, which has displayed similar psychometric properties to the 1970 version. In an extensive series of cross-validation analyses, which compared the participants of the current study with intellectually talented young adolescents (Schmidt et al., 1998), the psychometric properties of the SOV scales were found to be highly similar in their 1-year stability and construct validity across the two samples.

Personality. The Adjective Check List (ACL; Gough & Heilbrun, 1983) consists of 300 adjectives, in which participants select adjectives that describe them and skip adjectives that do not describe them. The 37 ACL scales assess a broad spectrum of personality dimensions extracted from the selected and omitted adjectives. Participants' scores for each scale were calculated against the norms for their gender.

Like the RIASEC and BIS scales, the manual for this instrument provides normative comparisons. Scale definitions and prototypical characteristics of high and low scorers are also provided in the ACL Manual (Gough & Heilbrun, 1983). The ACL includes scales from several psychological theories, including 15 scales from Henry Murray's need-press dispositions (Murray, 1938; achievement, dominance, endurance, order, intraception, nurturance, affiliation, heterosexuality, exhibition, autonomy, aggression, change,

succorance, abasement, deference), five scales from Berne's transactional analysis theory (Berne, 1966; critical parent, nurturing parent, adult, free child, adopted child), and four scales from Welsh's (1975) creativity and intelligence research (A1: high origence, low intellectance; A2: high origence, high intellectance; A3: low origence, low intellectance; A4: low origence, high intellectance).

There also are four "modus operandi scales" that measure how each person responds to the ACL (total number of adjectives checked, favorable adjectives checked, unfavorable adjectives checked, and communality), as well as nine topical scales that describe a variety of characteristics not affiliated with any theory (counseling readiness, self-control, self-confidence, personal adjustment, ideal self, creative personality, military leadership, masculinity, femininity). A number of these scales are described further in our Results section, while explicit definitions of all 37 scales are found in Supplement 1 of the online supplemental materials.

The ACL manual reports the following reliability data for the 37 scales (Gough & Heilbrun, 1983): Median coefficient alphas: males = .76, females = .75; median 6-month test-retest reliabilities: males = .65, females = .71.

Lifestyle and work preferences. The biographical survey included 13 lifestyle items that measure the relative importance of career, family, friends, and community, and 44 work preferences assessing various aspects of the conditions and nature of work environments (Ferriman et al., 2009). All questions had a 5-point scale with anchors at *not important* and *extremely important*. In addition, participants answered five items on how they spent their

time in graduate school (e.g., time on research, studying, leisure, teaching, and paid work).

Age 50: STEM Leadership

We classified participants as STEM leaders if they met any one of the six criteria in Table 1. We developed these criteria based on previous research and in consultation with distinguished experts in engineering and physics and with extensive knowledge of government STEM positions (see author note). Drawing on Thorndike's (1949, pp. 120–124) nomenclature of immediate, intermediate, and ultimate criteria, the outcomes in Table 1 constitute ultimate criteria. They encompass concrete and objective documentation of truly outstanding life accomplishments in STEM, thus meeting Cattell's (1957) standards for optimal L-Data (life record data). Following the Berkeley Studies of Creativity, Institute of Personality Assessment Research (IPAR; MacKinnon, 1965), we reasoned that if someone were truly eminent in their field, they should be publicly identifiable by leaders in the field.

We obtained criterion data through detailed Internet searches and cross-checks. In conducting searches, we referenced our participant database (Lubinski & Benbow, 2006), which included up-to-date idiographic information (e.g., last known occupation and any change of names). Rather than relying solely on follow-up surveys, this method served to maximize our entire sample of 714 participants. For very few participants, we were unable to find them in our Internet search and their current contact information in our database (nine males, 15 females). Given our method and criteria (see Table 1), we believe it unlikely that we missed a

Table 1
STEM Leader Criteria and Descriptive Information

STEM leader criteria _(Males n, Females n)	STEM leader	
	<i>n</i>	%
1. Tenured professor at a R1 university or international equivalent _(53, 28)	81	53.3%
Associate professor _(9, 9)	18	11.8%
Full professor _(44, 19)	63	41.4%
2. Senior executive at a Fortune 500 company _(2, 2)	4	2.6%
3. Senior position in government \geq GS-14 or equivalent scale _(6, 8)	14	9.2%
GS-14 _(0, 1)	1	0.7%
GS-15 _(2, 4)	6	3.9%
Executive scale _(0, 2)	2	1.3%
Other scales _(4, 1)	5	3.3%
4. Patents \geq 20 _(13, 5)	18	11.8%
5. Publications \geq 75 _(43, 19)	62	40.8%
Median number of publications	62	
Median <i>h</i> -index	23	
6. NIH/NSF grants \geq \$2.75 million _(38, 15)	53	34.9%
Median grant number	3	
Median grant total	\$958k	
7. Other ^a _(4, 4)	8	5.3%

Note. Parenthetical subscripts next to the criteria are the number of males and of females who met the criterion. Some participants met multiple leadership criteria (two criteria, $n = 46$, 30%, and three criteria, $n = 21$, 14%).

^a The criterion "Other" includes STEM leaders who are exceptions to the six criteria: (a) an astronaut; (b) a prominent science educator/writer who supervises PhD students and has multiple *Nature* publications; (c) a researcher who has multiple *Nature* and *Science* publications and over \$3 million in nongovernment grants; (d) a senior executive at a company who works on high-impact government projects; (e) a senior-level administrator for a U.S. military technical school; (f & g) two full professors at R2 universities (one in administration) with publication and funding totals just below our cutoffs; and (h) a research supervisor in a national research laboratory with numerous publications.

STEM leader. Their accomplishments are well-publicized (Eysenck, 1995; Murray, 2003; Simonton, 1994, 2014; Zuckerman, 1977) and objective. Therefore, the 24 participants not traceable through our Internet efforts were placed in the nonleader group.

In our searches, we recorded the current professional occupation(s) of our participants, and we used Publish or Perish (Harzing, 2007) to filter through Google Scholar information (i.e., to filter out results of publications with identical names or initials as our participants). We obtained participants' number of publications, number of patents, and *h*-indices. When available, we cross-referenced these Publish or Perish results with other online information (e.g., a participant's website or CV, ResearchGate, and Microsoft Academic). We also used the NIH and NSF databases to identify the number of grants and the amount of grant funding that our participants secured. Descriptive statistics of these accomplishments are reported in Table 1.

We classified eight participants as STEM leaders who had accomplishments that were exceptions to these six criteria. We classified them as STEM leaders based on our judgment and the expertise of our consultants. The note to Table 1 documents their exceptional individual accomplishments.

Ancillary Assessments

Following our analyses of the 25-year longitudinal data, an important set of ancillary analyses suggested itself. After reviewing the data on how our participants worked and allocated time in graduate school, we wondered whether their work habits continued in the same pattern after graduate school. Fortunately, we could answer this question with additional analyses of Age 35 data on 75% of our participants from their 10-year follow-up (Lubinski et al., 2006). The follow-up included questions about the average number of hours worked per week, days of travel for work per year, and days of vacation per year; moreover, participants reported on the number of hours they would be willing to work at their ideal job and days that they would be willing to travel at their ideal job. Although these analyses do not exhaust the entire sample, this ancillary analysis of 75% of our participants enabled us to assess the stability of these work behaviors reasonably well.

Data Analytic Approach

Our approach to data analysis involved a series of graphic profile and effect size displays across the different classes of attributes. Results fell into two major sections. The first analyzed profile differences between the STEM leaders and nonleaders within each gender. The second analyzed gender differences, which are presented in a series of rank-ordered effect size displays. Both sets of analyses are extensions and generalizations of a large literature on uncovering the psychological characteristics that distinguish isolated groups (see Humphreys et al., 1993, pp. 250–252, for an historical review). The talent development literature has leveraged empirical constellations emerging from this approach to conceptualize antecedents that give rise to contrasting developmental trajectories (Achter et al., 1999; Bernstein, Lubinski, & Benbow, in press; Ferriman et al., 2009; Lubinski, 2016; Lubinski & Benbow, 2006; Lubinski et al., 2014; Lubinski, Webb, Morelock, & Benbow, 2001; Makel, Kell, Lubinski, Putallaz, & Benbow, 2016; Wai, Lubinski, & Benbow, 2005, 2009; Webb, Lubin-

ski, & Benbow, 2002, 2007). Given the rarity of this sample and the comprehensiveness of the assessments, we wanted an approach that maximized descriptive flexibility and nuance. This approach accomplished that goal.

However, this data analytic approach does have a limitation. The issue with multiple testing is well-documented (Shaffer, 1995), in that each test contributes to the inflation of the Type I error (false-positive) rate. While there are proposed methods for correcting alpha levels to reduce Type I error, these methods may not solve the problem and reduce power (Asendorpf et al., 2013). As stated in Simmons, Nelson, and Simonsohn (2011), correcting alpha levels is a “nonsolution” because of the ambiguity around the researcher degrees of freedom in multiple testing, and it is unclear the degree to which each group of tests affects the false-positive rate.

Therefore, throughout, statistical significance is arbitrarily set at the $p < .05$ level, a familiar benchmark. We also note in figure captions and in text when $p < .01$. Yet, we do not attach substantive significance to any one contrast (cf., Ferriman et al., 2009; Lubinski et al., 2014; Lubinski, Webb et al., 2001). Our goal is to uncover *patterns* in the data in order to develop a profile of STEM leaders. We adopt the view that, in the early stages of theory construction, function-form and pattern are more informative than statistical significance (Meehl, 1978, 1990; Steen, 1988). We are at the early stages of the longitudinal study of eminence. This prospective study is a first attempt to detect attributes of STEM leaders among a sample of world-class STEM talent before they received state-of-the-art STEM graduate training. Therefore, a detailed accounting of all assessments is desirable. However, the conclusion of the results section does include a multivariate interpretation of our findings.

Results

Based on our criteria in Table 1, we found 152 STEM leaders (21% of our sample), of whom 64% were male. A chi-square test of independence of the difference between gender and leadership group was statistically significant, $\chi^2(1) = 11.65, p < .001$. The sample sizes of each leader group by gender are: male leaders = 97, male nonleaders = 271, female leaders = 55, female nonleaders = 291. Almost all STEM leaders had PhDs (96.7%), and the remainder had master's degrees. They held graduate degrees in: engineering (25.7%), chemistry (25.0%), physics (13.8%), biochemistry (10.5%), bioengineering (9.2%), mathematics (8.6%), biology (4.6%), computer science (1.3%), or interdisciplinary sciences (1.3%).

STEM Leaders and Nonleaders Comparisons

Educational history. We examined whether STEM leaders and nonleaders differed in their educational histories and accomplishments before graduate school (e.g., National Merit scholars and special educational programming; see Lubinski, Benbow et al., 2001, Tables 2 and 3, pp. 314–315). In general, there were no clear differences between leaders and nonleaders in their background and educational experiences (see Supplement 2 for more information). While these experiences are important for fostering talent and for admission into undergraduate and graduate schools (Benbow & Stanley, 1996; Lubinski, 2016; Wai, Lubinski, Benbow, &

Steiger, 2010), they did not appear to predict ultimate STEM leadership within this sample.

Ability. Participants' GRE scores revealed the exceptional intellectual abilities of this sample. The mean on the GRE-Q was 742.0 (*SD* = 58.2), one standard deviation from the top possible score of 800. Ultimately, we found ceiling effects across all GRE scores in this sample (see Supplement 3). Given this demonstrable caveat, we found only insignificant differences between STEM leaders and nonleaders on all GRE scores—GRE-V, GRE-Q, GRE-A, and the three-component GRE composite score. Clearly, this instrument is inappropriate for assessing individual differences in the mathematical reasoning ability of these participants; it does, however, document their exceptional ability.

Study of Values (SOV). Figure 1a displays SOV mean profiles for men and women, STEM leaders and nonleaders. The salient theoretical values for all groups revealed the validity of this instrument in identifying passion for STEM. We found no significant differences between STEM leaders and nonleaders with one

exception—a significant difference in theoretical values between male STEM leaders and nonleaders.

Holland themes (RIASEC). Findings on the RIASEC dimensions in Figure 1b paralleled those for the SOV, which showed convergent validity for both ipsative (SOV) and normative (RIASEC) measures. They display salient theoretical and investigative themes, respectively, for all groups. Although we found more similarities than differences between STEM leaders and nonleaders, male STEM leaders were significantly different on the investigative theme and the artistic theme. Overall, the RIASEC, like the SOV, reflected construct validity by capturing an orientation toward and passion for STEM pursuits among elite STEM graduate students. These are conspicuously atypical profiles from the general population; however, they are typical profiles for adolescents and young adults with passion for STEM.

Basic Interest Scales (BIS). Figures 2a and 2b display BIS profiles for men and women, leaders and nonleaders, respectively. These profiles highlighted the construct validity of the facets of

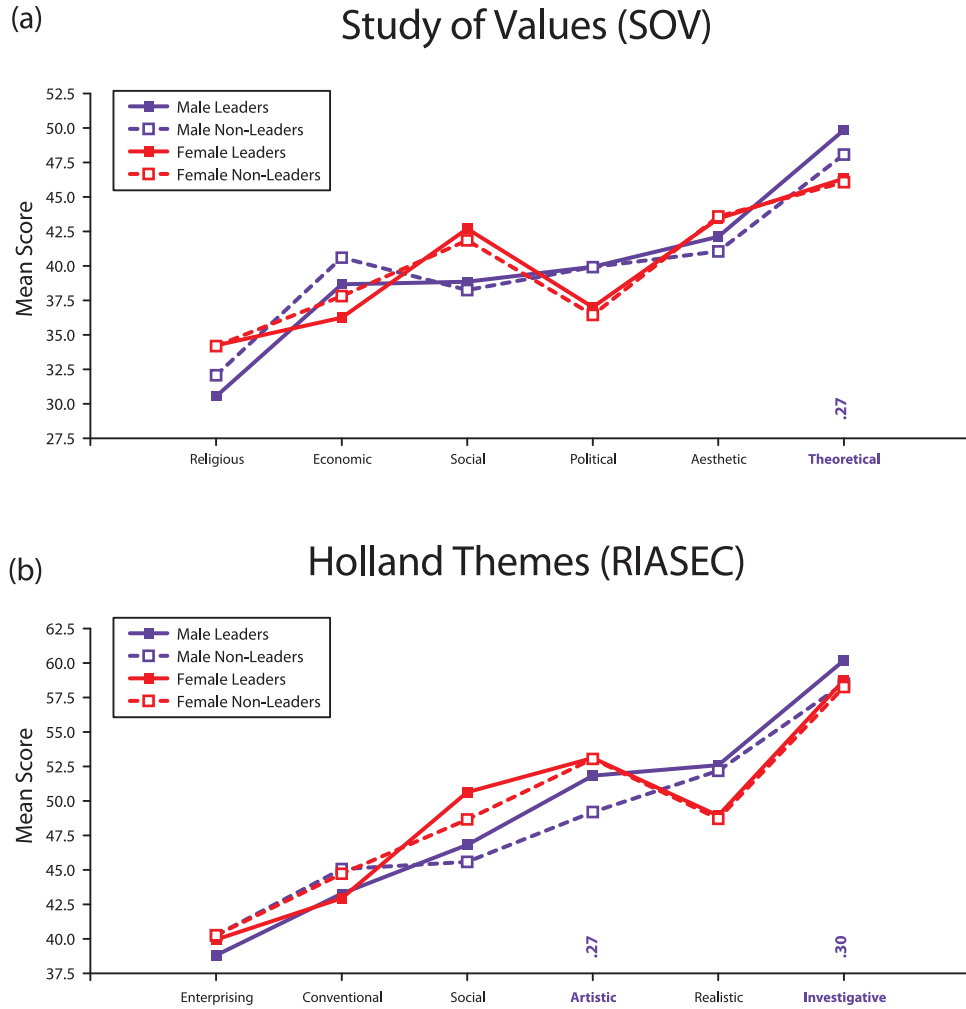


Figure 1. Means for SOV and RIASEC are displayed, and significant effect size differences (Cohen's *d*, *p* < .05) between leaders and nonleaders reported along the x-axis. Effect sizes for gender differences are reported in Figure 8. The colors indicate types of differences observed between the leader groups: (a) purple: differences for men only and (b) red: differences for women only.

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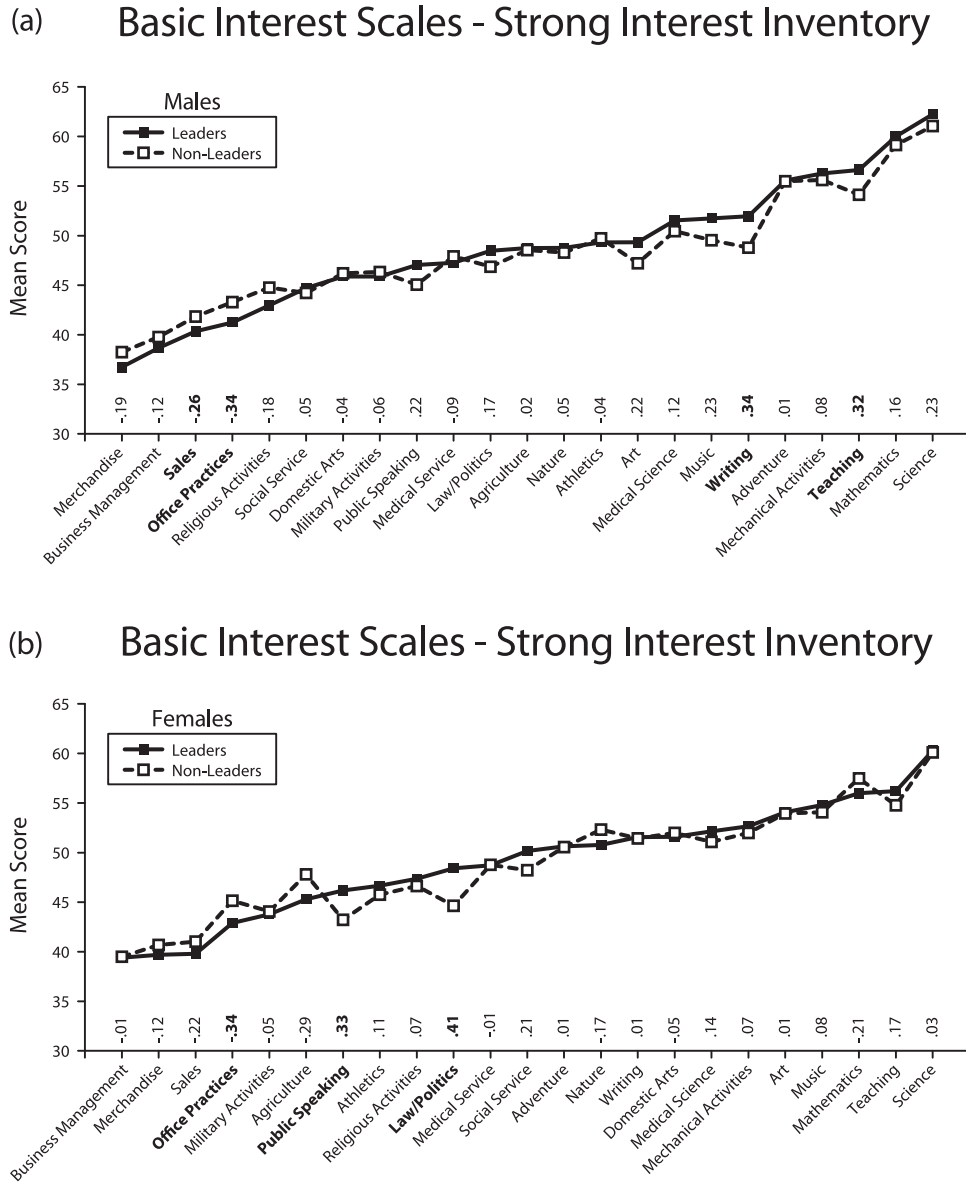


Figure 2. Means for all BIS scales are plotted for men (2a) and women (2b), and all effect size differences (Cohen's *d*) are reported along the *x*-axis. Significant differences are in bold ($p < .05$). The larger leader and nonleader differences ($p < .01$) are as follows: men: $d = \pm .32$; and women: $d = \pm .40$. Each graph is rank ordered by the means of the leader group. For comparing males and females with the same rank ordering, see Supplement 4.

participants' educational-occupational interests. Mathematics and science interests are dominant in profiles for all groups. Overall, there are more similarities than differences between leaders and nonleaders for both men and women; their profiles reflected an inordinate STEM focus distinct from the general population. For men and women, the high rank-order salience of mathematics, science, mechanical activities, and teaching revealed the passion that both STEM leaders and nonleaders have for STEM relative to other learning and work interests.

Personality. The ACL profiles of STEM leaders and nonleaders are shown in Figure 3a (males) and Figure 3b (females). Overall, their personality profiles depicted a dominant, self-

confident interpersonal presence. These individuals are oriented toward achievement and creativity, and relatively free of feelings of inferiority and the need for sympathy. When looking at group differences, both male and female STEM leaders had higher levels of dominance and self-confidence compared with nonleaders. STEM leaders were more assertive, cooperative, and reliable in their orientation toward work. Similar to previous results, male and female STEM leaders were lower on negative attributes (e.g., abasement, unfavorable adjectives, succorance) relative to the nonleaders, but the trend was less clear-cut. The more "socially potent" items best distinguished STEM leaders from nonleaders.

What emerges from our ACL analysis is that this sample is composed of an overabundance of highly effective individuals. However, the interpersonal presence of both male and female STEM leaders is more impressive than that of nonleaders. Self-confidence and dominance distinguish the leadership groups, and they have little penchant for neediness or soliciting sympathy from others; they are instrumentally effective doers on their own.³

Lifestyle and work preferences. Mean profiles of lifestyle preferences are in Figure 4, and work preferences are in Figure 5a (males) and Figure 5b (females). Overall, STEM leaders and nonleaders were similar in their lifestyle and work preferences. Ability to do well at work and being satisfied with work were among their most salient preferences. Our participants were ambitious, driven, and hardworking individuals.

Male leader versus nonleader contrasts. As graduate students, male STEM leaders rated being successful in their work, being a community leader, and having children as more important than male nonleaders. Male nonleaders preferred having more leisure time than male STEM leaders. These lifestyle preferences also mirrored differences in STEM leaders' and nonleaders' work preferences. Compared with male STEM leaders, male nonleaders preferred to work fewer hours, have stress-free work environments, and not to work on weekends. Male STEM leaders preferred jobs that provide challenges, support learning new things, use complex skills, and allow independent work. Taken as a whole, male STEM leaders were willing to work more hours and accept more challenges in their work compared with male nonleaders.

Female leader and nonleader contrasts. As graduate students, female STEM leaders rated finding the right person to marry as more important than female nonleaders did. However, both groups rated this lifestyle preference highly. There were few significant differences between female STEM leaders and nonleaders in their work preferences. The main significant difference was that female STEM leaders preferred independent work more than female nonleaders did.

Hours worked. Figure 6 shows the number of hours our participants spent on different activities in graduate school. These findings echoed the same pattern of results found for lifestyle and work preferences. Male nonleaders reported spending more time on leisure activities ($M = 19.2$ hr, $SD = 13.1$ hr) than male STEM leaders ($M = 15.3$ hr, $SD = 8.8$ hr), $t(226.2) = -3.02$, $p = .003$, $d = -.35$. The same pattern was found for female nonleaders spending more time on leisure activities ($M = 16.1$ hr, $SD = 10.2$ hr), relative to female STEM leaders ($M = 14.7$ hr, $SD = 10.1$ hr), but this contrast failed to reach statistical significance due to sample size limitations: $t(300) = -.89$, $p = .37$, $d = -.14$. To provide a more comprehensive analysis of graduate work hours, we added together time on research and studying and then tested for any differences. There were insignificant differences for the males; however, female STEM leaders reported working more hours in graduate school ($M = 58.4$ hr, $SD = 15.9$ hr) compared with female nonleaders ($M = 51.2$ hr, $SD = 19.0$ hr), $t(337) = 2.65$, $p = .009$, $d = .42$.

Ancillary assessments. Figure 7 displays the number of hours worked per week by participants when they were in their mid-30s. There were significant differences for both men and women. Female and male STEM leaders worked more hours than their did

gender-equivalent nonleader counterparts: male leaders ($M = 56.5$ hr, $SD = 9.5$ hr) and male nonleaders ($M = 49.4$ hr, $SD = 9.0$ hr), $t(274) = 5.63$, $p < .001$, $d = .77$; female leaders ($M = 51.9$ hr, $SD = 10.4$ hr) and female nonleaders ($M = 46.0$ hr, $SD = 12.7$ hr), $t(262) = 2.84$, $p = .005$, $d = .50$. When asked how many hours they were willing to work in their ideal job, there were, again, significant differences among both men and women. Male and female STEM leaders were willing to work more hours than their nonleader counterparts did: male leaders ($M = 57.9$ hr, $SD = 9.6$ hr) and male nonleaders ($M = 53.2$ hr, $SD = 10.5$ hr), $t(267) = 3.26$, $p = .001$, $d = .47$; female leaders ($M = 52.3$ hr, $SD = 9.3$ hr) and female nonleaders ($M = 46.4$ hr, $SD = 12.8$ hr), $t(82.90) = 3.65$, $p = .001$, $d = .53$.

We also asked participants how many vacation days that they took per year. For men, the nonleaders reported significantly more vacation days ($M = 16.2$ days, $SD = 11.1$ days) than STEM leaders ($M = 13.3$ days, $SD = 6.3$ days), $t(267) = -2.08$, $p = .04$, $d = -.32$; for women, nonleaders ($M = 16$ days, $SD = 13.5$ days) and leaders ($M = 14.2$ days, $SD = 4.7$ days) did not significantly differ on their vacation days ($d = -.18$, $p = .43$). These results were similar to the earlier male nonleader preferences for more leisure time and more leisure hours in graduate school. For women, STEM leaders traveled significantly more for work-related activities ($M = 16.4$ days, $SD = 15.9$ days) than nonleaders ($M = 9.8$ days, $SD = 19.3$ days), $t(256) = 2.10$, $p = .04$, $d = .37$; for men, there were minimal differences between leaders ($M = 18.3$ days, $SD = 18.7$ days) and nonleaders ($M = 17.1$ days, $SD = 30.6$ days; $d = .05$, $p = .76$). Similarly, female STEM leaders would be willing to travel significantly more in their ideal job ($M = 28.6$ days, $SD = 22.9$ days) than nonleaders ($M = 20.0$ days, $SD = 22.9$ days), $t(260) = 2.28$, $p = .02$, $d = .37$; for men, leaders ($M = 30.5$ days, $SD = 25.5$ days) and nonleaders ($M = 31.9$ days, $SD = 36.8$ days) had minimal differences on this preference ($d = -.05$, $p = .77$). Taken as a whole, STEM leaders are willing to work—and did work—more hours than nonleaders did, both in graduate school and subsequently in their careers.

Gender Differences

Ability. As noted earlier, the GRE is an inadequate tool for assessing the intellectual capabilities of our participants due to ceiling constraints. Nevertheless, male STEM leaders had significantly higher GRE-Q scores ($M = 756.8$, $SD = 50.0$) than female

³ The ACL is an established personality measure, and the second edition of its manual had appeared just before participants' Time 1 data were collected. However, we wanted to link these findings with the Big Five, which has become dominant in contemporary personality research. To link ACL findings to the Big Five personality traits, we compared the ACL scales to the Big Five, by referencing work that correlated the ACL to the NEO-PI (Piedmont, McCrae, & Costa, 1991), the NEO-PI-R (Craig, Loheidi, Rudolph, Leifer, & Rubin, 1998), and by matching the ACL adjectives to a Big Five adjective list (Saucier & Goldberg, 1996). In addition, we reviewed the literature that has compared the ACL with the Big Five personality traits (Craig et al., 1998; John, 1990; Piedmont et al., 1991). In general, these findings indicated that STEM leaders were higher in extraversion, agreeableness, and conscientiousness, and lower in neuroticism compared with nonleaders. A more detailed discussion of the relationship between the ACL and Big Five is in Supplement 5.

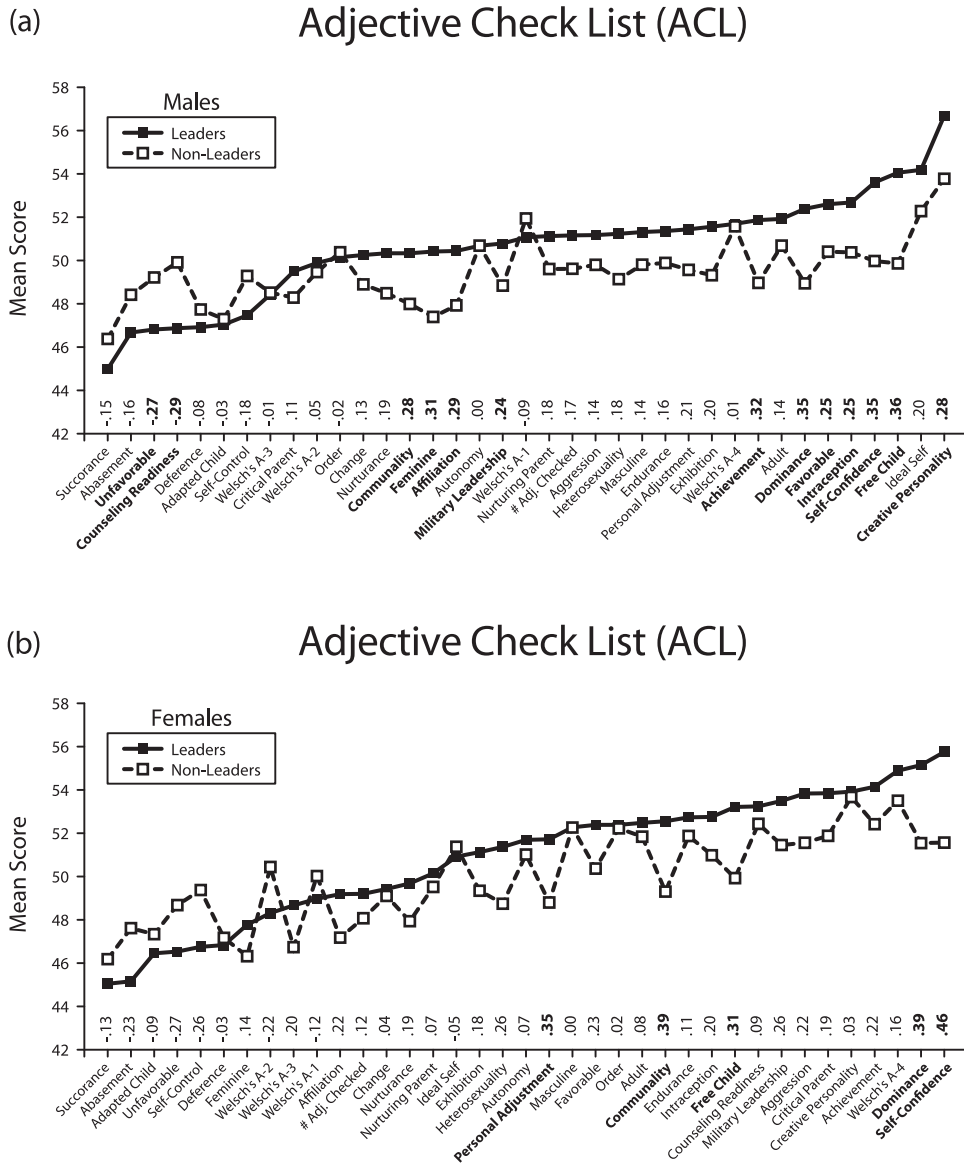


Figure 3. Means for all ACL scales are plotted for men (3a) and women (3b), and all effect size differences (Cohen's *d*) are reported along the x-axis. Significant differences ($p < .05$) are in bold. The larger leader and nonleader differences ($p < .01$) are as follows: men: $d = \pm .33$; and women: $d = \pm .39$. Each graph is rank ordered by the means of the Leader group. For comparing males and females with the same rank ordering, see Supplement 4.

STEM leaders ($M = 733.0, SD = 59.3$), $t(122) = 2.37, p = .02, d = .43$. Similarly, male nonleaders had higher GRE-Q scores ($M = 746.3, SD = 59.9$) than female nonleaders ($M = 734.6, SD = 57.9$), $t(482) = 2.18, p = .03, d = .20$.

Due to GRE-Q ceiling constraints, we tested whether there were gender differences in the proportion of men and women who attained a top possible score on the GRE-Q. For male STEM leaders and nonleaders, 29% and 30%, respectively, hit the GRE-Q ceiling with a score of 800; corresponding percentages for the female STEM leaders and nonleaders were 9% and 15%, respectively. We calculated proportion z tests between male and female STEM leaders and between male and female nonleaders. Both differences were significant: leaders: $z = 2.54, p = .03$, nonlead-

ers: $z = 3.79, p < .001$. Collectively, these findings suggest that while gender differences in mathematical reasoning are significantly different for both STEM leaders and nonleaders, the GRE-Q is unable to assess their precise magnitude.

SOV. Figure 8a displays gender differences in values. For STEM leaders, men and women significantly differed on four of the six values. Male leaders significantly held more theoretical and political values than female leaders, while female leaders significantly held more social and religious values than male leaders. For nonleaders, the men and women were significantly different on all six values. Male nonleaders held significantly more political, economic, and theoretical values than female nonleaders. Female nonleaders held significantly more social, aesthetic, and religious values than male

Lifestyle Preferences (Age 25)

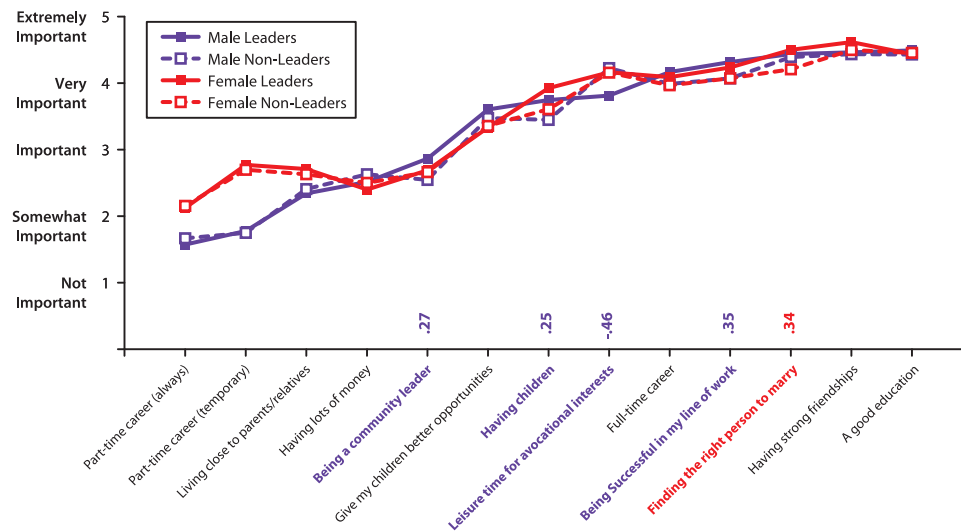


Figure 4. Participants rated lifestyle preference from 1 = not important to 5 = extremely important. Means for all lifestyle preferences are plotted, and significant effect size differences (Cohen's d , $p < .05$) between leaders and nonleaders are reported along the x-axis. Effect sizes for gender differences are reported in Figure 10. The larger leader and nonleader differences ($p < .01$) for men is $d = \pm .32$. The colors indicate types of differences observed between the leader groups: (a) purple: differences for men only and (b) red: differences for women only.

nonleaders. For additional information on gender differences in the SOV, see Supplement 6.

RIASEC. Figure 8b reports gender differences on the RIASEC. Men were significantly higher on the realistic theme than women were, for both STEM leaders and nonleaders. Women were significantly higher on the social theme than men were, for both STEM leaders and nonleaders. This pattern reflects that the robust gender difference in the people-versus-things dimension found in the psychological literature for decades (Su et al., 2009) holds even among STEM graduate students. Specifically, the realistic and the social themes are opposite poles within Holland's hexagon. Additionally, female nonleaders were higher on the artistic theme than were male nonleaders. For additional information on gender differences in the RIASEC, see Supplement 6.

BIS. Significant gender differences on the BIS scales are found in Figure 9. Across both STEM leaders and nonleaders, there is a pattern of differential pull in favor of STEM versus aesthetics and social service. Men are more interested in mathematics, adventure, science, mechanical activities, while women are more interested in domestic arts, social service, art, religious activities, merchandise, and music. Male STEM leaders, relative to female leaders, are particularly focused on mathematics and science; interestingly, these two effect size differences are over twice as large as the corresponding gender differences among nonleaders.

Lifestyle preferences. Gender differences in lifestyle preferences are depicted in Figure 10. The cluster of items for full-time and part-time work constitute the primary gender differences. The various items illustrate why it is useful to ask related questions in different ways, because both men and women prefer full-time work at comparable (and high) levels. As graduate students,

women were significantly more likely to prefer a part-time career compared with men (over various periods in life): part-time career always (leaders: $t(135) = -2.55$, $p = .01$, $d = -.44$; nonleaders: $t(520) = -4.46$, $p < .001$, $d = -.39$) or part-time career for a limited time (leaders: $t(132) = -4.29$, $p < .001$, $d = -.75$; nonleaders: $t(516) = -8.75$, $p < .001$, $d = -.77$). As shown by the means reported in Figure 4, while women rate these preferences as less important relative to other preferences, men rate their importance even lower than women did.

Work preferences. Figure 11 presents gender differences on work preferences. The pattern revealed a larger magnitude of differences between STEM leaders, relative to nonleaders. Compared with female leaders, male leaders prefer to travel, to take risks on the job, to work for a prestigious organization, and to have merit-based pay. Alternatively, compared with male leaders, female leaders preferred to receive feedback from supervisors, to know how well they are doing on the job, and to be satisfied with their work.

Hours worked and ancillary assessments. In graduate school, we found few gender differences in how men and women spent their time (see Figure 6). The only difference we found was that male nonleaders ($M = 19.2$ hr, $SD = 13.1$ hr) spent more time in leisure than female nonleaders ($M = 16.1$ hr, $SD = 10.1$ hr), $t(429.47) = 2.86$, $p = .004$, $d = .26$.

As other research on intellectually talented populations has revealed (Benbow, Lubinski, Shea, & Eftekhari-Sanjani, 2000; Ferriman et al., 2009; Lubinski et al., 2014), the Age 35 ancillary assessments revealed that men reported working and being willing to work more hours than women did (see Figure 7). These gender differences are consistent for both STEM leaders and nonleaders: STEM leaders hours worked, $t(112) = 2.40$, $p = .02$, $d = .46$;



Figure 5. Participants rated work preference from 1 = not important to 5 = extremely important. Means for all work preferences are plotted for men (5a) and for women (5b), and all effect size differences (Cohen's *d*) are reported along the x-axis. Significant differences ($p < .05$) are in bold. The larger leader and nonleader differences ($p < .01$) are as follows: men: $d = \pm .32$; and women: $d = \pm .40$. Each graph is rank ordered by the means of the Leader group. For comparing males and females with the same rank ordering, see Supplement 4.

nonleaders hours worked, $t(397.16) = 3.13, p = .002, d = .30$; STEM leaders ideal job hours, $t(111) = 3.06, p = .003, d = .59$; nonleaders ideal job hours, $t(411.22) = 5.97, p < .001, d = .58$.

Results Summary

Overall, the two sets of analyses in the Results section were complementary. They revealed how STEM leaders are similar to and different from nonleaders, and they highlighted impor-

tant gender differences and similarities. One interesting finding cutting across these analyses is that male STEM leaders are consistently farther removed from the other three groups (viz., male nonleaders, female STEM leaders, and nonleaders). Male STEM leaders had more salient STEM-specific attributes, fewer competing interests, and stronger focus on career success.

At the suggestion of a reviewer, we conducted a series of multi-variate analyses to cast further light on this idea. We ran four dis-

Hours Per Week Spent on Work and Leisure (Age 25)

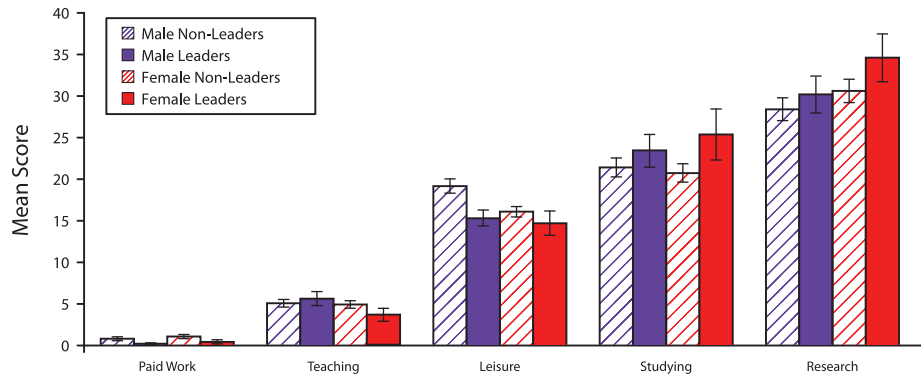


Figure 6. Mean number of hours per week that participants spent on various activities in their first or second year of graduate school. Error bars are ± 1 standard error of the mean.

criminant function analyses, using distinct groups of scales to determine how the four groups were psychologically distinguished in multivariate space. These four analyses used the following predictors: (a) GRE-Q, GRE-V, SOV, and RIASEC; (b) the 23 Basic Interest Scales; (c) the 13 lifestyle preferences; and (d) the 44 work preferences. The plots and structure matrices of these analyses are in Appendix A.

Each discriminant function analysis resulted in two independent and interpretable dimensions, which consistently separated the four groups in meaningful ways. Male STEM leaders pulled away from the other groups on different functions, which included STEM interests, non-STEM interests, and commitment to success at work. These findings suggest that compared with the other three groups, male STEM leaders were more focused on their passion for STEM and career success. These analyses showed why it is important to examine salient individual differences beyond STEM attributes alone—such as non-STEM interests, work preferences, and lifestyle preferences.

Discussion

Frequently, studies seek to explain extraordinary performance by uncovering unique and unknown qualities. Extraordinary performance is so rare that unique, unknown, and extraordinary determinants often are assumed to be at play. We took a different approach. We investigated the extent to which ultimate occupational differences among elite STEM graduate students are a function of “simply” more of known determinants (e.g., abilities, interests, personality) for developing scientific careers. We also assessed other characteristics known to give rise to eminence (lifestyle and work preferences). These individual differences can increase or decrease the likelihood of developing outstanding careers. As our study revealed, more than career-related abilities and interests are important to STEM leadership. Other interests and lifestyle preferences, priorities, and opportunities that compete for time must also be taken into account.

Hours Per Week Spent on Work (Age 35)

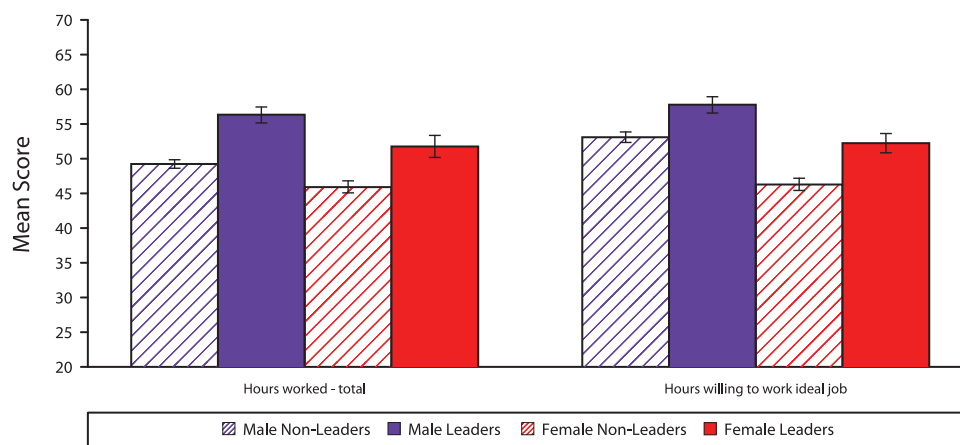


Figure 7. Mean number of hours per week that participants worked in their mid-30s and the mean number of hours per week that participants would be willing to work at their ideal job. Error bars are ± 1 standard error of the mean.

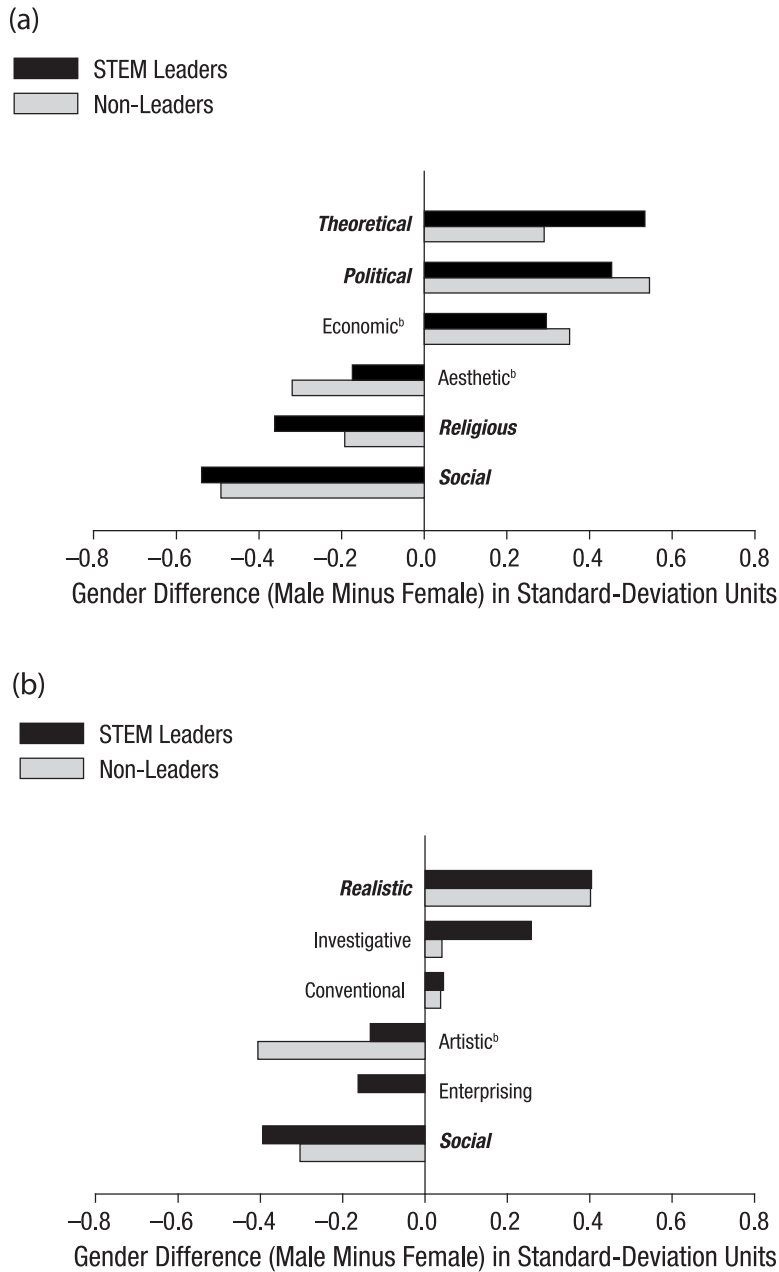


Figure 8. Gender differences (Cohen’s *d*) in the SOV (a) and RIASEC (b) for STEM leaders and nonleaders are plotted. If both leader and nonleader groups had significant gender differences ($p < .05$), the label is in bold and italicized. If only one of the groups had a significant gender difference, the superscripts indicate that the gender difference was significant for STEM leaders only (a) or for nonleaders only (b). The larger gender differences ($p < .01$) are as follows: STEM leaders: $d = \pm .45$; and nonleaders: $d = \pm .25$. The scales are rank ordered by the STEM leaders’ differences.

STEM Leaders Versus Nonleaders

The first purpose of this study was to determine whether individual differences among elite STEM graduate students predicted STEM leadership 25 years later. Across STEM leaders and nonleaders, there were more similarities than differences in ability, educational-occupational interests, and person-

ality. This finding is not surprising given the level of talent and background of these elite STEM graduate students. They had similar educational histories and educational opportunities up to the initial assessment, which enabled them to gain admission into elite STEM programs. While these participants selected environments corresponding to their abilities and interests, there were detectable personality differences among them that

mirror those seen in prior studies of outstanding engineers and physical scientists (Eiduson & Beckman, 1973; Eysenck, 1995; Jackson & Rushton, 1987; Roe, 1961, 1965; Super & Bachrach, 1957; Terman, 1954a, 1954b; Zuckerman, 1977). Male and female STEM leaders were more self-confident, dominant, and socially poised than nonleaders. On both the high and the low end of their ACL profiles (Figures 3a and 3b), clusters of adaptive and maladaptive attributes pull STEM leaders away from nonleaders.⁴

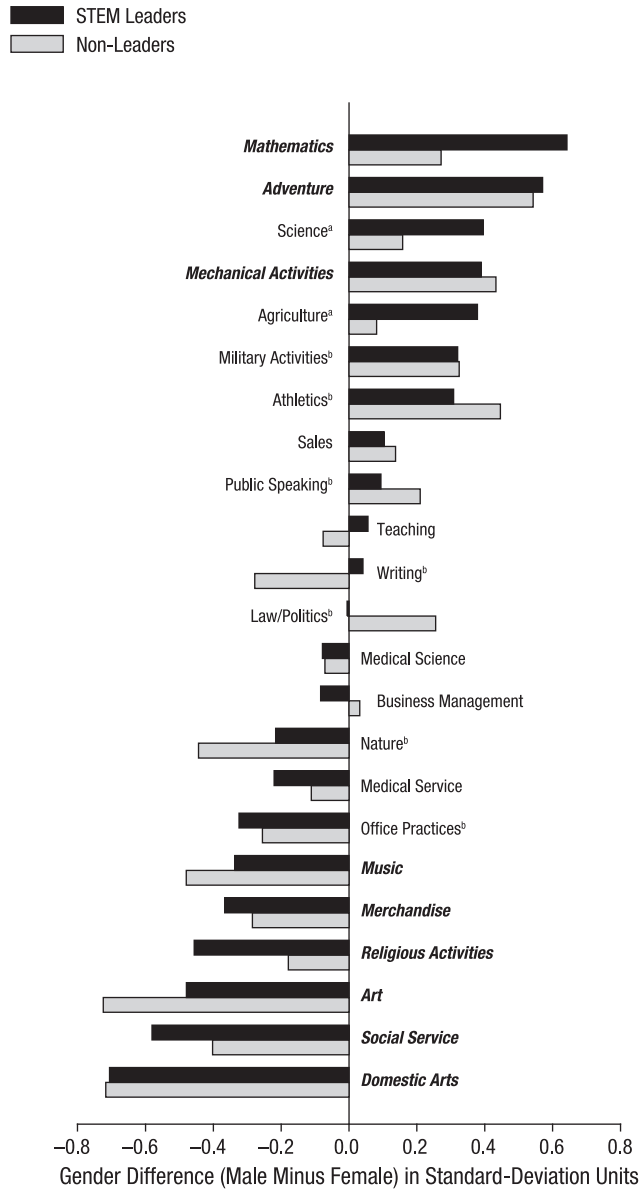


Figure 9. Gender differences (Cohen's *d*) in the BIS for STEM leaders and nonleaders are plotted. If both leader and nonleader groups had significant gender differences ($p < .05$), the label is in bold and italicized. If only one of the groups had a significant gender difference, the superscripts indicate that the gender difference was significant for STEM leaders only (a) or for nonleaders only (b). The larger gender differences ($p < .01$) are as follows: STEM leaders: $d = \pm .45$; and nonleaders: $d = \pm .25$. The scales are rank ordered by the STEM leaders' differences.



Figure 10. Gender differences (Cohen's *d*) in lifestyle preferences for STEM leaders and nonleaders are plotted. If both leader and nonleader groups had significant gender differences ($p < .05$), the label is in bold and italicized. If only one of the groups had a significant gender difference, the superscripts indicate that the gender difference was significant for STEM leaders only (a) or for nonleaders only (b). The larger gender differences ($p < .01$) are as follows: STEM leaders: $d = \pm .45$; and nonleaders: $d = \pm .25$. The items are rank ordered by the STEM leaders' differences.

As with other forms of eminence (Eysenck, 1995; Gardner, 1993; Jackson & Rushton, 1987; Murray, 2003; Roe, 1961, 1965; Simonton, 1988, 2014), STEM leaders and nonleaders differed in their work commitment (Eysenck, 1995; Gardner, 1993; Jackson & Rushton, 1987; Murray, 2003; Roe, 1961, 1965; Simonton, 1988, 2014). We also found differences between STEM leaders and nonleaders in their lifestyle and work preferences. Even as graduate students, STEM leaders were more dedicated to their careers than nonleaders. While these preferences may change over time (Ferriman et al., 2009; Geary, 2010; Hakim, 2006; Pinker, 2008; Rhoads, 2004), it is important to note that these personal attributes and priorities assessed early in their graduate training predicted STEM leadership 25 years later.

Arguably, the most agreed upon finding in the talent development literature is the inordinate amount of time outstanding contributors in any profession devote to their careers (Ericsson,

⁴ When we shared their ACL profiles with Robert Hogan (personal communication, March 7, 2018), he remarked that the STEM leaders are unlikely to have accomplished what they have done primarily as a function of their personal qualities measured by the ACL. However, given the pattern captured by the ACL assessments, the nonleaders may have been limited somewhat in the attributes captured by the ACL (given their abilities, background, and training).

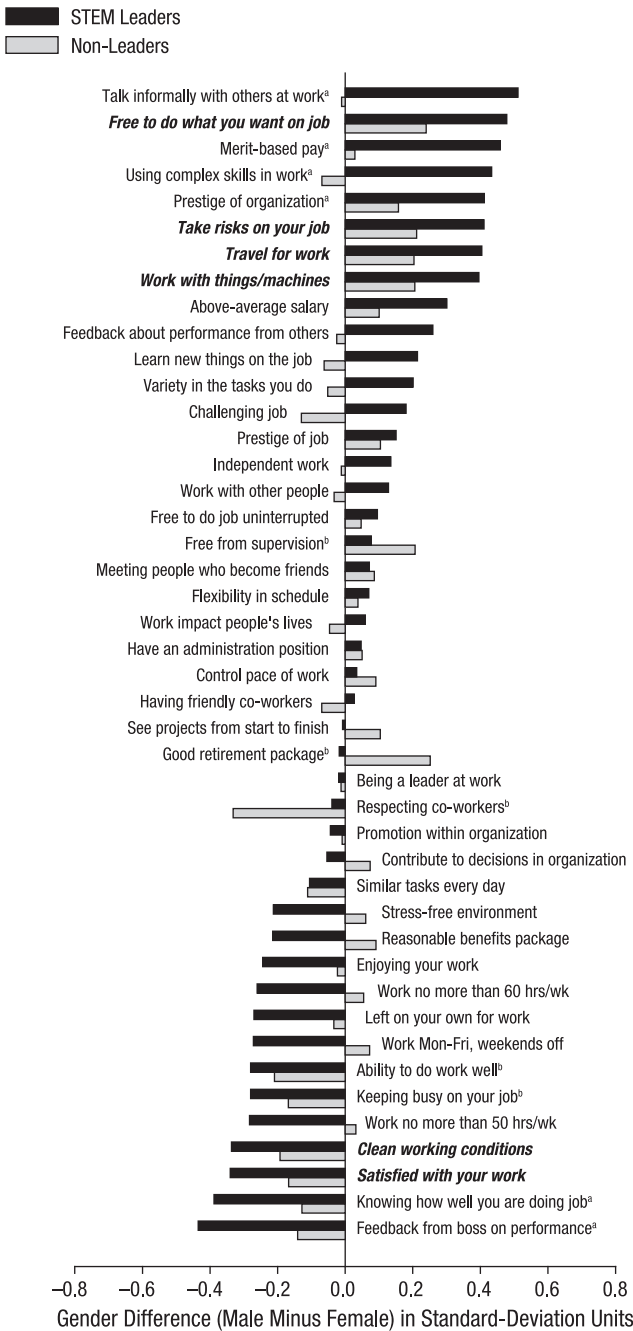


Figure 11. Gender differences in work preferences for STEM leaders and nonleaders are plotted. If both leader and nonleader groups had significant gender differences ($p < .05$), the label is in bold and italicized. If only one of the groups had a significant gender difference, the superscripts indicate that the gender difference was significant for STEM leaders only (a) or for nonleaders only (b). The larger gender differences ($p < .01$) are as follows: STEM leaders: $d = \pm .42$; and nonleaders: $d = \pm .23$. The items are rank ordered by the STEM leaders' differences.

Charness, Hoffman, & Felovich, 2006; Eysenck, 1995; Gardner, 1993; Lubinski & Benbow, 2006; Simonton, 1994, 2014; Zuckerman, 1977). In one respect, STEM careers are more time-intensive than many others, due to the rapid growth of

STEM knowledge. Advancing STEM knowledge is especially demanding because workers need to keep their skills up-to-date. This process requires assimilation and adaptation to rapid conceptual and technical change. Economists have labeled this phenomenon “knowledge decay” (Goldin, 2014; McDowell, 1982). STEM leaders likely navigate these challenges through their commitment and passion for work, a pattern that continued into their early careers. STEM leaders worked more hours than nonleaders did, and they expressed a willingness to work more hours in their ideal job relative to nonleaders. This resonates with the TWA framework wherein talent, interests, and passion combine to facilitate committed relationships with cutting-edge STEM environments.

Some unique within-gender comparisons are also important. Among men, STEM leaders differed significantly from non-leaders on investigative interests and theoretical values, $d = .30$ and $d = .27$, respectively. These differences alone are surprising given that these interests and values are the most related to STEM—highlighting the uniqueness of the male STEM leaders. Moreover, when we ran a series of discriminant function analyses (see Appendix A), a particularly compelling STEM focus among male STEM leaders crystalizes. Across four discriminant function analyses, male STEM leaders consistently move away from the other three groups in various combinations of personal qualities that are indicative of STEM focus and career success.

Before concluding this section, we note that even though we found differences between STEM leaders and nonleaders, there were also many similarities between them. They all had well-defined STEM interests and were mathematically talented. Nonleaders typically had respectable STEM careers. They held diverse STEM jobs, including managers in STEM companies, CEOs of start-up businesses, and teachers of varying educational levels. Nonleaders also included people who were leaders outside of STEM. While these “nonleaders” are not the chief drivers of STEM research and innovation, they are essential to the success of the STEM enterprise and society as a whole.

Gender Differences

The second purpose of this study was to examine gender differences. We found evidence mirroring well-documented gender differences in the workforce generally. While our sample started with comparable numbers of men and women in exceptional STEM graduate programs, we found significant gender differences in STEM leadership—approximately two thirds (64%) of our STEM leaders were male. Yet, the women in our sample gained admission into elite STEM graduate programs, and they clearly have the abilities, background, interests, and personality to achieve highly in STEM (Lubinski, Benbow et al., 2001).

How did women and men in our sample differ from each other when they began STEM graduate study? While their overall profiles of men and women in this sample were similar on a variety of dimensions, there were several significant gender differences that are psychologically noteworthy due to their collective intensity. Men had higher scores on the GRE-Q compared with women, and men were twice as likely to earn top possible scores on the GRE-Q. This finding suggests that gen-

der differences in mathematical reasoning ability were likely underestimated in this study (Wai, Cacciario et al., 2010).⁵

In addition, these elite STEM graduate students had conspicuous gender differences in general and specific educational-occupational interests as well as in their life values. For example, men had more focused STEM interests than women did, particularly in mathematics, science, and mechanical activities. While females did hold conspicuous STEM interests as shown by the salience of STEM among the Basic Interest Scales (Figure 2b), they were not quite as intense as the males were (see Figure 9). Similar to findings in the general population and in samples of intellectually talented adolescents (Lubinski et al., 2014; Su et al., 2009), women in elite STEM programs had more diverse interests in art, music, domestic arts, and social service than men did. Given the breadth of interests among these women relative to men, they are likely to be interested in pursuing a more heterogeneous set of high-power career options. For example, many intellectually talented women are excelling in academic administration and multiple leadership roles—jobs that require a diverse set of skills and responsibilities, and thus call for a more balanced pattern of interests.

Women also differed somewhat in their lifestyle and work preferences when compared with men, as observed in other studies of intellectually talented populations (Ferriman et al., 2009; Geary, 2010; Gino et al., 2015; Hakim, 2006, 2011; Lubinski et al., 2014; Pinker, 2008; Rhoads, 2004). Women placed greater emphasis on living close to parents, assigned a greater level of importance to part-time work, clean working conditions, and valued more feedback on their work. Men were more likely to value the prestige of the organization that they were working for and traveling as part of their work. While an individual item difference between men and women tells little, when these differences are aggregated, the response pattern becomes clear and tells a meaningful story. Even among our STEM leaders, women worked fewer hours than men did, and they wanted to spend more time in leisure. This finding was somewhat surprising as work with tenured and tenure-track faculty showed small gender differences in the hours worked per week (Ceci et al., 2014). Individuals did choose to invest their time differently, which has ripple effects in personal and career accomplishments (Abelson, 1985; Rosenthal & Rubin, 1982).

Taken as a whole, these results capture meaningful gender differences among people with tremendous STEM potential and who experienced elite STEM graduate training programs. Group differences, which are simply aggregated individual differences, are likely to play out in the same way as they do for individuals. Individuals and groups who vary on these attributes will likely differ somewhat in the activities they find most personally meaningful and rewarding both within and outside of STEM leadership positions. Nevertheless, it is important to stress that individual differences between groups are typically modest compared with the individual differences within groups. As such, it is best for designing optimal talent development procedures to treat each person as an individual, not as a member of some group (Assouline, Colangelo, & Vantassel-Baska, 2015; Benbow & Stanley, 1996; Corno, Cronbach, et al., 2002; Gottfredson, 2003; Lubinski, 1996, 2010). These procedures involve structuring interventions and opportunities in accordance with one's individuality.

Considerations in Studying Eminence Longitudinally

Psychological differences between STEM leaders and nonleaders and between men and women define how individuals experience and navigate their work environment. Life is ipsative. Each individual has a finite amount of time to allocate each day. STEM leaders consistently spent more time developing their careers. These decisions likely led them to have different work and life experiences, augmenting changes in their skill levels, interests, and personality (Pressey, 1955; Roberts, Caspi, & Moffitt, 2003). STEM leaders invested their time by seeking opportunities to refine their skills, likely leading to further professional opportunities (Ceci et al., 2014; Ceci & Williams, 2011; Geary, 2010; Gino et al., 2015; Judge, Klinger, & Simon, 2010; Lubinski & Benbow, 2000, 2001; Simonton, 1999). This process is generalizable to broader psychological frameworks, such as “niche building” (Asbury & Plomin, 2013; Scarr, 1996; Scarr & McCartney, 1983). By self-selecting and even constructing environments for themselves, individuals sharpen the distinctive features of their individuality, shaping the opportunities they experience. What is true for individuals on these indicators is also true for groups. Among populations with exceptional STEM talent, this process likely begins early in development.

For example, well before college our participants had outstanding mathematical reasoning abilities and they enjoyed many educational opportunities in STEM (cf. Lubinski, Benbow et al., 2001, Tables 2 and 3, pp. 314–315). Such a background among top STEM students is likely more disproportionate today, as educational opportunities for intellectually talented adolescents have mushroomed over the past 25 years (Assouline et al., 2015; Lubinski, 2016); moreover, this phenomenon has emerged in the popular press (Tyre, 2016). Elite STEM graduate students likely bring more sophisticated expertise and knowledge to their disciplines than our participants did in the early 1990s.

Among intellectually talented samples, individual differences in abilities, interests, and personality are in place before they enter high school (Achter et al., 1996, 1999; Humphreys et al., 1993; Schmidt et al., 1998; Wai et al., 2005, 2009; Webb et al., 2002, 2007). These gifted young adults begin to structure their learning environment and seek opportunities that reflect their abilities and

⁵ To reveal how inadequate GRE ability assessments are for psychological research on adult populations with exceptional abilities, consider the GRE data, as it is utilized in the United States. Among prospective U.S. graduate students, scores on the GRE-V and GRE-Q subtests are reported on a 600-point scale, ranging from 200 to 800. A midrange score of 500 on GRE-V denotes the 59th percentile, whereas 500 on GRE-Q represents only the 18th percentile! Thus, half of the score range on GRE-Q is devoted to the bottom 18% of the distribution. GRE-Q scores of 700 or more, falling in only a sixth of the range, are obtained by 40% of test takers. A top possible score of 800 lies only at the 92nd percentile. This was recently pointed out explicitly (Lubinski, 2018, p. 251), and is reinforced in a related figure by Ceci, Ginther, Kahn, and Williams (2018, p. 35). The percentile information is also reported by the Educational Testing Service (2017) on their website. Contrast this with the selection procedures used by Bill Gates in developing Research Institute-Beijing, which Thomas Friedman (2005, pp. 266–267) details in his book, *The World Is Flat*, or the selection procedures implemented at the Indian Institute of Engineering, which Fareed Zakaria (2011, pp. 205–206) describes in *The Post-American World*. These two cross-cultural examples reflect procedures corresponding to recent advances on the multidimensionality and scope of human potential among people occupying the world's leading centers for STEM innovation (see Figures 1 through 4 in Makel et al., 2016).

interests in early adolescence (Ceci, 2000; Ceci et al., 2014; Webb et al., 2002, 2007). As educational opportunities expand in depth and breadth, a more multidimensional array of expertise and knowledge distinguishes them from their intellectual peers who have other interests. Such differences facilitate further development along specialized paths. It also may lead to other individuals providing support in furthering their development. These differences, therefore, have implications for assimilating more sophisticated knowledge and expertise during graduate training and beyond because more outstanding students are operating from a deeper knowledge base (Ackerman & Lakin, 2018; Lubinski, 2016; Pressey, 1955).⁶

Limitations

We used the GRE to measure ability, which was suboptimal for this sample. While effective in predicting success in graduate school (Kuncel & Hezlett, 2007, 2010), the GRE had range restriction and ceiling effects for our elite STEM graduate students. In addition, we did not measure spatial ability (Lubinski, 2004; Ozer, 1987). Decades of past research have documented that spatial ability predicts STEM careers and creative accomplishments beyond verbal and mathematical abilities (Gohm et al., 1998; Kell, Lubinski, Benbow, & Steiger, 2013; Uttal et al., 2013; Wai et al., 2009). Evidence suggests that people with greater spatial ability relative to verbal ability are more likely to develop STEM expertise compared with people with greater mathematical ability relative to verbal ability (Humphreys et al., 1993; Wai et al., 2009). Correcting these limitations through future research would be worthwhile.

Finally, the purpose of this study was to determine the psychological significance of the individual differences that students with outstanding potential for STEM bring to world-class graduate training programs. We did not assess here why their lifestyle preferences and priorities changed over time, or whether they needed to change as they faced varying conditions in their work and personal lives. For example, parenthood places disproportional demands on women, and women may decide to work fewer hours to balance family and work (Ferriman et al., 2009; Geary, 2010; Hakim, 2006; Liben & Coyle, 2014; Lubinski et al., 2014; Wang, & Degol, 2017; Pinker, 2008; Rhoads, 2004). In our Age 35 data, we found that female STEM leaders (48%) were less likely to be parents than male STEM leaders (64%). The decisions that women face regarding if and when to have children have more influence on their career decisions relative to men (Ceci et al., 2014).

Conclusion

Can we predict who will become a STEM leader at midlife using individual differences data from mid-20s? The answer is “yes.” While important, developing STEM leaders requires more than identifying individuals with exceptional passion and talent for STEM along with the right personality and placing them in outstanding graduate training programs. It also requires assessing the pull of other things and activities. Life involves making trade-offs. One’s personality and preferences lead one to choose, often in small steps, one activity over another. These decisions accumulate over time and compound. Decades later, they lead to very different life outcomes—in this case, STEM leadership versus other life possibilities. There is no right or wrong, as different people require different things to create a mean-

ingful and satisfying life. Not all exceptional STEM graduate students are willing to give up doing other things to become a STEM leader. For them, that comes at too high of a cost. For others, there seems to be little or no cost. And they are the ones who become STEM leaders, most likely to create the STEM innovations that drive our conceptual economy.

⁶ As an example, in longitudinal analyses conducted at Georgia Tech (Ackerman, Kanfer, & Beier, 2013), the 2002 entering freshman cohort had completed an average of 2.84 AP exams, and by 2009 matriculating students had completed an average of 4.14 (with nearly 5% of entering students completing 10 or more AP exams)! Intellectually talented students are now arriving at college with a deeper knowledge base than ever before, particularly at elite institutions. The individual differences examined here constitute broad outlines of how people prefer to tailor salient aspects of their individuality to the environment. As critical as these individual differences are for understanding the development of STEM eminence (and different types of eminence), it is also important to assess the expertise and knowledge that modern students bring to their college experience. For students who ultimately become STEM leaders, they likely enter college as psychologically different from the student body norm as students who aspire to and ultimately become outstanding professional athletes and musicians. Each of these populations brings to their college experience layers of individual differences, which motivated them to select differential opportunities (and motivate specialized environmental niches to seek them out), which ultimately distinguish them further from their peers in terms of specialized expertise. Some take a highly concentrated path, like Steve Wozniack, whereas others, like Steve Jobs, seek a bigger picture (Isaacson, 2011).

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Appendix A

Discriminant Function Analyses

A subtle tendency ran through our analyses. The personal attributes of male STEM leaders consistently pulled away from the other three groups. This appeared in different sets of personal attributes, suggesting that these combined attributes might increase their chances of developing an outstanding STEM career. Across our analyses, male STEM leaders possessed stronger STEM interests, fewer competing interests, and rated career success as more important than the other three groups. As this pattern emerged, we wanted to examine how different sets of variables align in a multivariate analysis to uncover more general themes.

We conducted four discriminant function analyses to see how multiple predictors could differentiate our four groups. The results of all four analyses are plotted in Figure A1. The four panels in Figure A1 each display a two-dimensional graph with the *x*-axis for discriminant function 1 (F1) and the *y*-axis discriminant function 2 (F2). The bivariate means for each group on these functions were plotted. Each group's bivariate mean was surrounded by an ellipse, defined by ± 1 standard error of the mean on each of the functions.

The following predictor sets were selected for analyses: (a) Panel A includes 11 predictors from the GRE, SOV, and RIASEC; (b) Panel

B includes the 23 Basic Interest Scales; (c) Panel C includes the 13 lifestyle preferences; and (d) Panel D includes the 44 work preferences. For all four analyses, no more than two discriminant functions were statistically justified to account for the variance distinguishing these four groups. In Appendix B, we report the salient weights defining each pair of functions (in truncated structure matrices), along with the labels that we assigned to these functions based on their salient weights. These are followed by statistical details in Appendix C, including the accounted for between-groups variance. The full structure matrices are found in Supplement 7.

These analyses were psychologically illuminating. Before reading further, readers are encouraged to examine the four graphs and their corresponding truncated structure matrices. What is clear is that each group fell in the same location within each graph. Across all four plots, Function 1 highlighted the gender differences that we found, and Function 2 highlighted the differences between STEM leaders and nonleaders. Each graph was scaled such that high scores on Functions 1 and 2 constitute a region indicative of either personal characteristics known to give rise to outstanding

(Appendices continue)

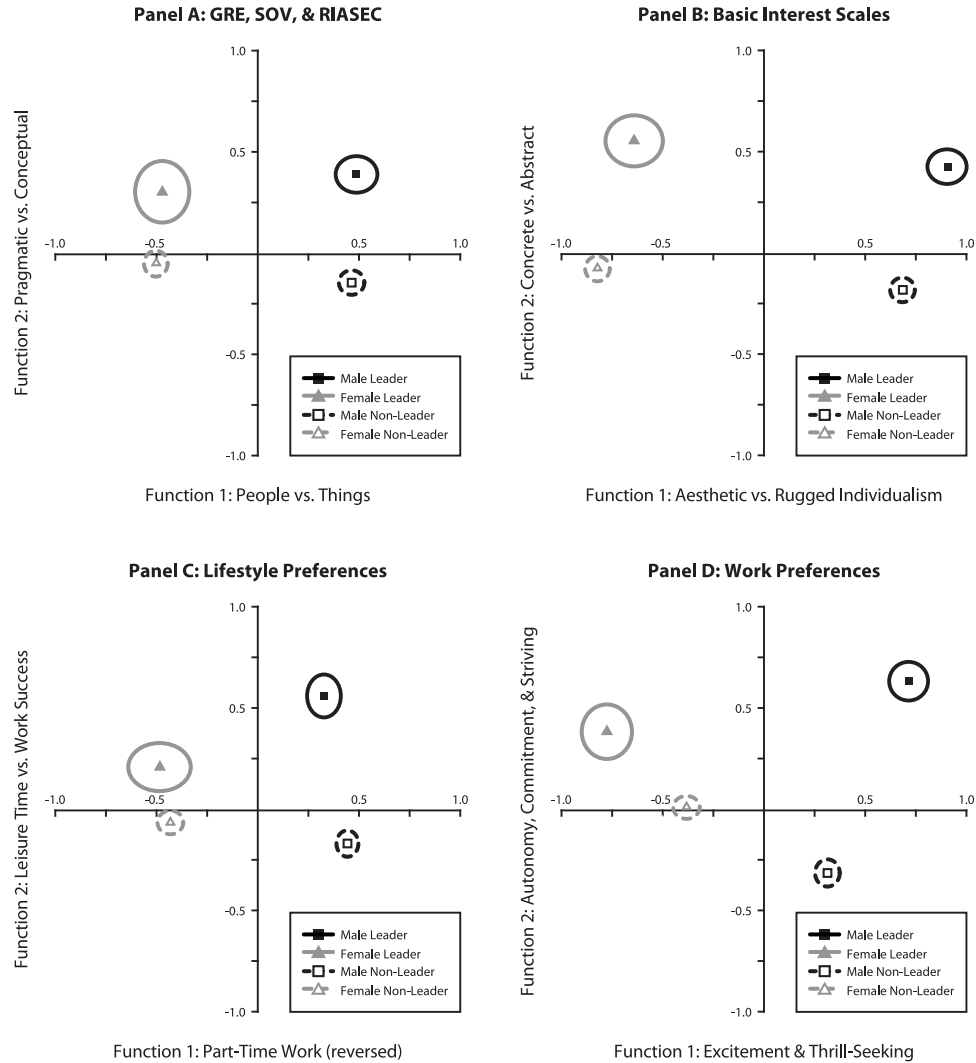


Figure A1. Discriminant function analyses using different sets of predictors to differentiate the four groups in a common multivariate space.

careers in general or personal attributes known to give rise to outstanding STEM careers in particular. Other locations within these graphs constitute regions indicative of less consequential careers or careers less fully concentrated on STEM.

In the first analysis (Panel A), the GRE, SOV, and RIASEC scales converge on a well-known people-versus-things dimension (F1) and an independent dimension characterized by a pragmatic-versus-conceptual orientation (F2). In the second analysis (Panel B), the Basic Interest Scales form an aesthetic-versus-rugged individualism (F1) and a concrete-versus-abstract (F2) dimensions. The third analysis (Panel C), the lifestyle preferences form a part-time work (reversed; F1) and a leisure time-versus-work success (F2) dimen-

sions. In the final analysis (Panel D), work preferences forms an excitement and thrill-seeking (F1) and an autonomy, commitment, and striving (F2) dimensions. Male STEM leaders consistently emerge in the NE quadrant across these figures whereas the female STEM leaders tend to occupy the NW quadrant. This suggests that male and female STEM leaders bring a somewhat different psychological orientation to their leadership roles. Just as this study has focused on the multidimensionality and scope of the individual differences of elite STEM graduate students, these findings suggest the importance of future lines of research into the multidimensionality, nature, and scope of STEM leadership positions themselves.

(Appendices continue)

Given that there were four groups in these analyses (male STEM leaders, female STEM leaders, male nonleaders, and female nonleaders), three canonical discriminant functions were possible. We considered all three; however, for all of the analyses, the third discriminant function accounted for an insignificant increase in the between-groups variance (see below). Therefore, only two discriminant functions were retained and plotted. We presented the test statistics for each analysis, along with a truncated structure matrix with the salient weights for each function. The complete structure matrices are found in Supplement 7.

Panel A: GRE, SOV, and RIASEC

For Panel A, the test of all three functions together was highly significant (Wilks' $\Lambda = 0.768$, $p < .001$), indicating that they explained 23.2% of the between-groups variance, and that at least one discriminant function (Function 1) was significant. However, the test of just discriminant Functions 2 and 3 was insignificant. Of the between-groups variance explained by the three discriminant functions, Function 1 accounted for 83.7% of the variance, Function 2 accounted for 12.9% of the variance, and Function 3 accounted for 3.4% of the variance. Even though Function 2 only approached statistical significance, it was retained and plotted because it was interpretable and fit the pattern found in the three subsequent analyses.

Panel B: Basic Interest Scales (BIS)

For Panel B, the test of all three functions together was highly significant (Wilks' $\Lambda = 0.558$, $p < .001$), indicating that they explained 44.2% of the between-groups variance, and that at least one discriminant function (Function 1) was significant. The test of just discriminant Functions 2 and 3 was also significant (Wilks' $\Lambda = 0.913$, $p < .034$), indicating that at least discriminant Function 2 is useful, but the test for Function 3 alone was not significant. Of the between-groups variance explained by the three discriminant functions, Function 1 accounted for 87.2% of the variance and Function 2

accounted for 9.0% of the variance. Because Function 3 was not statistically significant and accounted for only 3.9% of the between-groups variance, only Functions 1 and 2 were used.

Panel C: Lifestyle Preferences

For Panel C, the test of all three functions together was highly significant (Wilks' $\Lambda = 0.772$, $p < .001$), indicating that they explained 22.8% of the between-groups variance, and that at least one discriminant function (Function 1) was significant. The test of just discriminant Functions 2 and 3 was also significant (Wilks' $\Lambda = 0.932$, $p = .002$), indicating that at least discriminant Function 2 is useful, but the test for Function 3 alone was not significant. Of the between-groups variance explained by the three discriminant functions, Function 1 accounted for 74.1% of the variance and Function 2 accounted for 21.3% of the variance. Because Function 3 was not statistically significant and accounted for only 4.6% of the between-groups variance, only Functions 1 and 2 were used.

Panel D: Work Preferences

For Panel D, the test of all three functions together was highly significant (Wilks' $\Lambda = 0.697$, $p < .001$), indicating that they explained 30.3% of the between-groups variance, and that at least one discriminant function (Function 1) was significant. The test of just discriminant Functions 2 and 3 was also significant (Wilks' $\Lambda = 0.849$, $p < .028$), indicating that at least discriminant Function 2 is useful, but the test for Function 3 alone was not significant. Of the between-groups variance explained by the three discriminant functions, Function 1 accounted for 55.9% of the variance and Function 2 accounted for 27.1% of the variance. Function 3 accounted for 17.0% of the between-groups variance, but it was not statistically significant (due to the number of predictors in this analyses). Therefore only Functions 1 and 2 were used.

Appendix B

Truncated Structure Matrices

Panel A: GRE, SOV, and RIASEC

Variable	F1	F2
SOV-social	-.50	.21
Social	-.31	.31
Artistic	-.34	.42
Realistic	.41	.06
SOV-theoretical	.37	.38
Investigative	.11	.45
SOV-economic	.32	-.48
Conventional	.01	-.43

(Appendices continue)

Panel B: Basic Interest Scales (BIS)

Variable	F1	F2
Domestic arts	-.45	.08
Art	-.40	.36
Music	-.26	.37
Social service	-.26	.26
Nature	-.25	.03
Teaching	.00	.40
Writing	-.11	.37
Public speaking	.15	.38
Law/politics	.16	.39
Office practices	-.20	-.43
Sales	.05	-.40
Adventure	.34	-.10
Mechanical activities	.27	-.10
Athletics	.26	-.07

Panel C: Lifestyle Preferences

Variable	F1	F2
Having a part-time career for some time period	-.88	-.10
Having a part-time career always	-.46	-.17
Having leisure time to enjoy avocational interests	.03	-.63
Being successful in my line of work	-.03	.51

Panel D: Work Preferences

Variable	F1	F2
Freedom to do pretty much what you want on the job	.37	.24
Traveling as part of the work you do	.31	.15
Being able to take risks on your job	.30	.10
The prestige or reputation of the organization for which you work	.29	.23
Working with things (e.g., machines) as part of your job	.28	.00
Clean working conditions	-.27	-.13
Working no more than 50 hr per week	-.14	-.46
Working Monday through Friday with your weekends free	-.10	-.43
Working no more than 60 hr per week	-.11	-.41
Stress free work environment	-.08	-.39
A good retirement package	.14	-.32
Challenging job	.02	.39
Opportunity to learn new things on your job	.07	.39
Respecting your colleagues or coworkers	-.20	.37
Being left on your own to do your work	-.05	.37
The ability to do your work well	-.19	.27

Note. Bold values indicate the salient weights for each function. The following labels were used for interpreting Function 1 (F1) and Function 2 (F2) for each panel. For Panel A, F1: people-versus-things and F2: pragmatic-versus-conceptual. For Panel B, F1: aesthetic-versus-rugged individualism and F2: concrete-versus-abstract. For Panel C, F1: part-time work (reversed) and F2: leisure time-versus-work success. For Panel D, F1: excitement and thrill-seeking and F2: autonomy, commitment, and striving.

(Appendices continue)

Appendix C

Discriminant Function Analyses

Panel A: GRE, SOV, and RIASEC

Discriminant function	Eigenvalue	% of variance	Canonical correlation	Wilks' Λ	p
1	.244	83.7%	.443	.768	<.001
2	.037	12.9%	.190	.954	.109
3	.010	3.4%	.099	.990	.807

Panel B: Basic Interest Scales (BIS)

Discriminant function	Eigenvalue	% of variance	Canonical correlation	Wilks' Λ	p
1	.636	87.2%	.623	.558	<.001
2	.065	9.0%	.248	.913	.034
3	.028	3.9%	.165	.973	.580

Panel C: Lifestyle Preferences

Discriminant function	Eigenvalue	% of variance	Canonical correlation	Wilks' Λ	p
1	.208	74.1	.415	.772	<.001
2	.060	21.3	.237	.932	.002
3	.013	4.6	.113	.987	.622

Panel D: Work Preferences

Discriminant function	Eigenvalue	% of variance	Canonical correlation	Wilks' Λ	p
1	.217	55.9	.423	.697	<.001
2	.106	27.1	.309	.849	.028
3	.066	17.0	.249	.938	.394

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