NON-ABILITY CORRELATES OF THE SCIENCE-MATH TRAIT COMPLEX: SEARCHING FOR PERSONALITY CHARACTERISTICS AND REVISITING VOCATIONAL INTERESTS

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To my family

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SUMMARY

The trait complex approach (Ackerman & Heggestad, 1997) makes it possible to study the individual holistically by taking account of various individual differences at the same time, such as abilities, personality, motivation, and vocational preferences. Recently, Kanfer, Wolf, Kantrowitz, and Ackerman (2010) provided support for taking a whole-person approach in predicting academic performance. They also showed the incremental role of non-ability predictors over the role of ability predictors. Objectives of the present study were to further explore the non-ability variables of the science/math trait complex.

Identifying the personality correlates of the science/math trait complex was the first objective. Investigation results yielded four personality factors as correlates of the complex, which play important roles for engineers and scientists at different stages of the vocational track: toughmindedness was the personality marker of the science/math trait complex and was associated with intending to pursue a STEM career; achievement and control were associated with academic success in STEM majors; and cognitively-oriented behavior was associated with more cognitively challenging pursuits, such as attending STEM competitions and planning to go on to graduate school.

The second purpose was to revisit the vocational interests associated with the science/math trait complex and the Science, Technology, Engineering, and Mathematics (STEM) groups. A new measure was introduced, referred to as the STEM Interest Complexity Measure, which measures interests towards engaging in increasingly complex tasks in the Numerical, Symbolic, Spatial, and STEM-related Ideas domains.

This assessment was developed to assess the *level* of vocational interests, in addition to the traditionally assessed *direction* of vocational interests (Holland, 1985). Thus, the new measure was hypothesized to add incremental variance over traditional interest assessments in predicting vocational criteria.

Validation of the new STEM Interest Complexity Measure showed adequate construct and concurrent criterion-related validities. Construct validity was established by demonstrating associations between the new measure and measures of the direction of interests, cognitive abilities, intelligence as personality, and learning goal orientations. Support for the new measure's criterion-related validity was found by demonstrating that the measure discriminates between majors, and predicts vocational criteria (i.e., college achievement in STEM, attachment to STEM fields, major satisfaction, and one's intentions to chose a complex STEM career). With dominance analyses, it was shown that STEM Interest Complexity was the most important vocational assessment in the prediction of criteria. Results support the assertion that vocational interest inventories can be improved by incorporating the level of complexity dimension.

Finally, a science/math trait complex composite score, including toughmindedness, achievement, control, and the STEM Interest Complexity composite in addition to the previously determined ability, interest, and self-concept associates, showed moderate associations with STEM-related vocational criteria. The non-ability individual differences, which were the focus of the present study, added to the conceptualization and predictive utility of the science/math trait complex.

CHAPTER I

INTRODUCTION

Most research in the fields of educational and organizational psychology has studied individual differences in cognitive ability, personality, and vocational interests separately in relation to academic or work criteria. Associations between interests and personality (e.g., Barrick, Mount, & Gupta, 2003), between personality and cognitive abilities (e.g., Snow, 1977; Wolf & Ackerman, 2005), between interests and cognitive abilities (e.g., Carless, 1999; Randahl, 1991) and between all three domains (Ackerman & Heggestad, 1997) have also been investigated. Starting with Snow (1977), several investigators proposed that historically distinct trait constructs could be developing in relation to each other, thereby giving rise to constellations of dispositions.

Commonalities among dispositions do not imply the mere use of one domain in predicting outcomes. Researchers such as Snow (1987), Ackerman (1997), and Lubinski (2000) posited that individual behavior is not determined by a single trait and therefore suggested that studies should go beyond domain-constrained investigations to understand how dispositions in different domains combine to determine educational or job-related outcomes. Furthermore, research on dispositional variables has shown that certain abilities, personality traits, and interests coexist and form different clusters of traits. Such trait clusters have been referred to as "aptitude complexes" by Snow (1977) and "trait complexes" by Ackerman (1997). Snow proposed the aptitude complexes to show how combinations of traits produce differential educational outcomes. Ackerman's theory of trait complexes views the emergence of these clusters from a developmental perspective and proposes that an individual's interests develop in accordance with his or her personality and cognitive abilities and as a result different interest, personality, and ability clusters emerge (e.g., Ackerman & Heggestad, 1997). What is common to these perspectives is that they view the different dispositional domains as separate constructs that must be considered together in relation to outcomes.

1.1 Ackerman's Model of Trait Complexes

Ackerman's model of trait complexes refers to the amalgamation of individual differences variables in different domains based on commonalities between them. Ackerman and his colleagues have performed a series of analyses investigating the relationships between cognitive abilities, personality traits, and vocational interests. Based on the meta-analyses of personality-intelligence relationships, and the literature reviews of interest-personality together with interest-ability relations, Ackerman and Heggestad (1997) suggested a model of trait complexes. The initial model included four traits complexes: social, clerical/conventional, science/math, and intellectual/cultural.

The trait complexes model was empirically validated through a series of studies conducted by Ackerman and his colleagues (Ackerman, 2003; Ackerman, Bowen, Beier, & Kanfer, 2001; Ackerman & Rolfhus, 1999; Rolfhus & Ackerman, 1999). Findings indicated that the social trait complex represents commonalities among social and enterprising interests and the personality traits of extraversion, social potency, social closeness, and spatial self-concept. The clerical/conventional trait complex includes perceptual speed abilities, conventional interests, and the personality traits of control, conscientiousness, and traditionalism. The intellectual/cultural trait complex includes crystallized intelligence and ideational fluency, artistic and investigative interests, verbal self-concept, and the personality traits of absorption, openness to experience, and typical intellectual engagement (TIE; Goff & Ackerman, 1992).

1.1.1 The Science/Math Trait Complex

The science/math trait complex is characterized by commonalities among spatial abilities, math reasoning abilities, realistic interests, and investigative interests (Ackerman & Heggestad, 1997). Follow-up studies based on educated samples of students or adults further supported the pattern of correlates (Ackerman, 2003; Ackerman et al., 2001). Only the science/math trait complex was found to be positively and significantly associated with math abilities (r = .30), spatial abilities (r = .40), and fluid intelligence (r = .20 for the undergraduate sample and above .30 for the freshman sample). The complex correlated less with verbal abilities and crystallized intelligence (around r = .10) than did other trait complexes.

Math, science, and spatial self-concepts and self-estimated abilities loaded on a factor associated with the science/math trait complex. A composite of realistic interests, critical thinking skills, and experiences related to the math, science, technology, mechanical, and spatial domains correlated with math self-concept/self-estimates (r = .20) and with spatial self-concept/self-estimates (r = . 41) (Ackerman & Wolman, 2007). Further investigations of the science/math trait complex showed substantial positive correlations with the physical science knowledge domain (r = .40) which included astronomy, biology, chemistry, electronics, physics, and technology (Ackerman, 2003).

Ackerman and colleagues included personality constructs in the analysis of trait complexes, based on either Tellegen's MPQ (1982) or the NEO Five-Factor Inventory

(Costa and McCrae, 1992). None of the personality constructs were found to be correlated with the science/math trait complex.

1.2 Holland's Theory of Vocational Choices

Based on different activities, competencies, self-concepts, and vocational preferences Holland (1959, 1985, 1997) classified both interest and work environments into six categories, denoted by the acronym RIASEC: realistic, investigative, artistic, social, enterprising, and conventional. According to the typological approach, a person's interest or the work environment is portrayed by either one dominant theme or a combination of two or three themes forming a pattern. Holland (1985) provided descriptions of the types as follows.

"[The realistic type] enjoys working with hands, tools, machines, electronic equipment. (…) Prefers concrete, practical, and structured solutions or strategies as opposed to clerical, scholarly, or imaginative activities" (pp. 21-22).

"[The investigative type has] a preference for activities that entail the observational, symbolic, systematic, and creative investigation of physical, biological, and cultural phenomena. (…) Sees self as analytical, curious, scholarly, and having broad interests. Enjoys reading or thinking about solutions to problems" (pp. 22-23).

Artistic types enjoy creating art forms; social types enjoy activities involving interacting with others or helping others; enterprising types also prefer interacting with others but with a focus on attaining organizational goals or economic gain; and conventional types display a preference for manipulating and organizing data.

In addition to work environments, Holland (1959) also suggested a "level hierarchy." In this theory, occupational level was synonymous with the status of a particular occupation in the occupational class, or the status of the position the individual holds in the occupation. Holland posited that, within a major class of occupations (i.e. the RIASEC environments), the individual's choice of a particular occupation was a function of the individual's abilities and self-evaluations to perform effectively in the chosen environment. Nevertheless, the applications of Holland’s theory have focused more on the major role of interest assessment in career counseling (i.e., the use of the Unisex Edition of the American College Testing Interest Inventory - UNIACT; see Swaney, 1995). Self-evaluations of abilities have been integrated into interest assessments (e.g., Campbell, Hyne, & Nilsen, 1992; Harmon, Hansen, Borgen, & Hammer, 1994; Holland, 1985, 1994; Kuder & Zytowski, 1991; Prediger & Swaney, 1995). However, a more direct approach that would tap an individual’s interest and preference to enter an occupation at differing levels of the occupational hierarchy has not been addressed.

1.3 Objectives of the Present Study

The studies on trait complexes have shown that cognitive, affective, and conative traits cluster together and that clusters are differentially related to individual differences in domain knowledge (Ackerman, 2003). As argued by Ackerman (2003), such trait complexes may aid in better understanding how traits come together to yield different styles of learning by determining the direction and level of effort toward knowledge and skill acquisition, and hence different levels of educational outcomes. This view is illustrated in Ackerman’s (1996) theory of “intelligence-as-process, personality, interest, and intelligence-as-knowledge” (PPIK). In the PPIK theory, Ackerman states that different interest, personality, and ability clusters emerge as a result of interests developing in accordance with personality and cognitive abilities. More specifically, potential implications of undertaking a multiple-trait perspective as represented by trait complexes are outlined by Ackerman (1997) as related to: a) determining the motivation of an individual to perform a task and willingness to continue performance in spite of failures, b) determining vocational choice, c) the prediction of academic performance through the development and expression of knowledge, and d) the prediction of occupational success and work outcomes such as turnover intentions and job satisfaction.

Research on trait complexes did not reveal a relationship between any personality traits with the science/math trait complex. As an attempt to identify personality correlates of this trait complex characterized by realistic and investigative interests and math and spatial abilities, I reviewed the literature with a particular focus on: (1) more recent findings between interest-personality and cognitive ability-personality relations that pertain to the underlying theme of the complex and (2) personality correlates of occupational groups that show ability and interest characteristics associated with the science/math trait complex: engineers and scientists.

Another focus of the present study concerns vocational interests associated with the science/math trait complex. Interests related to the Science, Technology, Engineering, and Mathematics (STEM) related vocational groups may not be well represented by just indicating a *direction* of interest towards the realistic and investigative themes. These themes span occupations that vary in complexity level (Gottfredson, 1986; Gottfredson & Holland, 1996). Assessing direction of interests may not adequately capture an individual's intention to engage in tasks that are characteristic of higher occupational levels, which are cognitively more complex and demanding.

The purpose of the present study was twofold: (1) to investigate the personality correlates of the science/math trait complex; and (2) to revisit the nature of realistic and investigative interests in relation to STEM occupations, and to design and validate a new assessment (i.e. STEM Interest Complexity) to capture an individual's desire to engage in more complex and cognitively demanding tasks, characteristic of STEM occupations.

1.4 Outline of the Dissertation

The remainder of the dissertation is organized as follows: In Chapter 2 the focus is on reviewing the literature to find potential personality correlates of the science/math trait complex. In Chapter 3 I focus on revisiting the nature of current vocational interest assessments that pertain to the science/math trait complex, and point to a new direction of assessing vocational interests. In Chapter 4 I summarize the basic objectives of the present study and also describe how the proposed new vocational assessment was developed. In Chapter 5 I present the hypotheses and method of Study 1 concerning testing the hypothesized personality correlates and pilot testing the newly developed vocational interest assessment: The STEM Interest Complexity scales. In Chapter 6 I present the Study 1 results pertaining to the hypothesized personality correlates of the science/math trait complex and also the initial results obtained from the new interest measure. In Chapter 7 I provide a discussion of the Study 1 results on personality. In Chapter 8 I present the Study 2 hypotheses and method for validating the STEM Interest Complexity scales and in Chapter 9 I present the results of the validation. In Chapter 10 I provide a discussion of the validation results and the contribution to the literature. Finally, in Chapter 11 I summarize the conclusions derived from the findings of both studies as they pertain to the personality and vocational interests of STEM groups.

CHAPTER II

SEARCHING FOR THE PERSONALITY CORRELATES OF THE SCIENCE/MATH TRAIT COMPLEX

In line with the aim of investigating potential personality correlates of the science/math trait complex, I reviewed the more recent literature of the interrelationships among interests, personality, and cognitive abilities, and the personality of individuals entering engineering- and science-related vocational areas.

2.1 Personality and Interests

Consistent with the purpose of the current study, interest-personality associations are summarized with a focus on investigative and realistic interests, and the basic interest scales (Campbell, Hyne, & Nilsen, 1992; Hansen & Campbell, 1985) associated with the realistic and investigative interests.

Meta-analytic investigation of the personality-interest associations was carried out based on Holland's interest themes and the Five Factor Model (FFM) of personality. The FFM measures five global factors of personality: extraversion, agreeableness, openness to experience, neuroticism, and conscientiousness (Digman, 1990). For each global factor, six lower-level facets were suggested (Costa & McCrae, 1995). Meta-analysis results indicated that investigative interests were moderately ($\hat{\rho}$ = .25) associated with openness to experience (Barrick, Mount, & Gupta, 2003). Sullivan and Hansen (2004) found that the variance between investigative interests and openness to experience was mostly accounted for by the openness to ideas facet (r = .35) and inversely by the openness to feelings facet (*r* = -.24). Opennes to ideas was also significantly correlated with the science and math Basic Interest Scales, with correlations ranging from .24 to .47, and negatively correlated with openness to feelings, with magnitude of correlations ranging from .23 to .26 (Larson & Borgen, 2002; Sullivan & Hansen, 2004).

Some significant correlations were also observed between realistic interests and the FFM facets. De Fruyt and Mervielde (1997) found the anxiety, depression, and vulnerability facets of neuroticism; the assertiveness and excitement seeking facets of extraversion; the openness to ideas and openness to feelings facets of openness to experience; the tender-mindedness facet of agreeableness; and the achievement-striving and self-discipline facets of conscientiousness were associated with realistic interests. The magnitude of significant correlations did not exceeded .23 and the median was .16. The highest facet-level association was observed with openness to ideas (*r* = .22) but only for women (Carless, 1999; DeFruyt & Mervielde, 1997; Larson & Borgen, 2002). Openness to ideas was also found to be significantly correlated (around *r* = .25) with the nature, adventure, and mechanical Basic Interest Scales (Larson & Borgen, 2002).

When personality theories other than the FFM are considered, realistic and investigative interests also had small to moderate associations with various personality dimensions. Based on the MPQ (Tellegen, 1982), realistic interests were associated negatively with constraint and harm-avoidance, and positively with absorption. Investigative interests were related negatively to harm-avoidance, and positively to positive emotionality, social potency, achievement, and absorption. Magnitude of relations ranged from .21 to .34 (Kanfer, Ackerman, & Heggestad, 1996; Larson and Borgen, 2002). Similarly, a more recent meta-analysis of Staggs, Larson, and Borgen

(2007) found that the MPQ harm-avoidance was negatively and significantly related both to realistic (r = -.31) and investigative (r = -.19) interests, and negatively related to the Basic Interest Scales of agriculture, military activities, mechanical activities, and science, with the magnitude of correlations ranging from .20 to .28. The MPQ achievement scale was found to be associated with investigative interests, and the science and math Basic Interest Scales, with associations ranging from .21 to .27. Nonetheless, it should be pointed out that this meta-analysis only included studies that assessed personality based on the MPQ. Based on the 16PF (Cattell, Eber, & Tatsouka, 1970), Conn and Rieke (1994) reported that realistic interests were related negatively to warmth, sensitivity, apprehension, and anxiety, and positively to toughmindedness. Investigative interests were related negatively to warmth, sensitivity, and extraversion, and positively to reasoning. Magnitude of significant correlations ranged from .20 to .45. Finally, investigative interests were found to be moderately associated (r = .42) with Typical Intellectual Engagement (TIE) (Kanfer et al., 1996), a construct developed by Goff and Ackerman (1992) which refers to "a desire to engage and understand the world, interest in a wide variety of things, and a preference for a complete understanding of a complex topic or problem, a need to know" (p.539).

In sum, investigative interests were most strongly associated with openness to ideas, TIE, and reasoning (r range = .35 to .45), and to a lesser extent negatively associated with harm-avoidance and with traits related to interpersonal interactions, such as openness to feelings, warmth, sensitivity, and extraversion. Realistic interests had positive associations with openness to ideas, absorption, toughmindedness, and negative associations with harm-avoidance, openness to feelings, warmth, and sensitivity.

2.2 Personality and Cognitive Abilities

This section focuses on the positive relationships between personality traits and cognitive abilities, which from a developmental perspective, have been suggested to have developed in the long run (e.g., Ackerman & Heggestad, 1997). Accordingly, two related personality constructs appear to be related to cognitive abilities: openness to experience and typical intellectual engagement.

In their meta-analysis, Ackerman and Heggestad (1997) found moderate associations between openness to experience and crystallized intelligence (Gc) ($\hat{\rho}$ = .30) and general intelligence (*g*) ($\hat{\rho}$ = .33). In addition to the FFM traits, TIE significantly correlated with most abilities including *g* (*r* = .22), Gc (*r* = .35), and math-numerical abilities (*r* = .09), but did not significantly correlate with fluid intelligence (Gf).

The association between openness to experience and cognitive abilities was confirmed in studies that followed the meta-analysis of Ackerman and Heggestad (1997). Moderate associations were reported in these studies (e.g. Carless, 1999; Moutafi, Furnham, & Crump, 2003) that ranged from .27 to .45. Facet-level analysis showed that openness to ideas was a positive predictor of abilities, with the highest weights observed of all the FFM predictors (Moutafi et al., 2003). Moutafi et al. (2003) also reported a significant correlation (*r* = .15) between openness to experience and Gf, as measured by the Watson-Glaser Critical Thinking Appraisal Test in an adult working sample. The authors argued that as Gf cannot be expanded and is less susceptible to environmental influences, the direction of this significant relationship could be explained as intelligence influencing a sub-factor of openness, which is ideas. Individuals with higher *g* or Gf have wider interests due to their ability to handle novel experiences, encouraging openness.

2.3 Personality Correlates of Engineers and Scientists

The following findings are derived from studies that compared various engineering or scientist groups to other groups on the basis of various personality factors. First, I summarize these findings by organizing them based on the common themes of personality characteristics. Following this, I provide a more detailed account of the studies, with their sample characteristics and the effect sizes indicating how strong the engineering groups differ from other groups based on the personality factors.

2.3.1 A Preference for Things and Structure

The most notable personality traits that distinguish engineers and scientists from members of other groups parallel the things/people dimension of Prediger (1982) and are characterized by a preference for dealing with things rather than interacting with people, accompanied by a tendency to thinking as opposed to feel. Izard's (1960) comparison of freshman engineers with students from the arts and sciences based on Edwards's Personal Preference Schedule (EPPS, Edwards, 1959) revealed that engineers were significantly lower on the scales of intraception, nurturance, and affiliation. Beall and Bording (1964) replicated this finding by showing that engineers preferred things rather than people. Izard's analysis of occupational samples revealed a similar pattern. A sample of 81 currently employed engineers was compared to the norming sample of the EPPS, comprised of 750 male liberal arts students. Engineers had a lower need for abasement, showing an impersonal and authoritarian approach; had a lower need for affiliation; had a lower need for intraception, showing low analytic interest in people and an avoidance of introspection; and had a lower need for nurturance, showing a preference for objects rather than people.

Williams (1997) compared the personalities of freshmen engineers to those of the members of a college normative sample of 1,600 students, based on the Millon Index of Personality Styles (Millon, 1994), which assesses motivational aims, cognitive modes, and interpersonal behaviors. Williams reported that among women, the normative sample displayed higher levels of the agreeing, accommodating, nurturing, intuiting, and feeling traits, whereas the engineer sample displayed higher levels of the thinking trait compared to the normative group. Among men, however, no significant differences were reported between groups in terms of traits related to interacting with people. Harris (1994) also reported that engineers were lower on nurturance compared to nursing and psychology students, though no effect size or descriptive statistics were provided.

The preference for dealing with things as opposed to interacting with people is related to the preference for structure and certainty as opposed to ambiguity. Beall and Bording (1964) showed that the preference of engineers for things rather than people paralleled a preference for the objective, practical, and certain. Izard's (1960) study based on the EPPS comparing engineering students to students from the arts and sciences indicated that engineers had a higher need for order, showing a preference for structure and avoidance of ambiguity. Harris (1994) reported that engineering students had a higher need of cognitive structure assessed based on the Personality Research Form (PRF), than did nursing and psychology students. Brown and Joslin (1995) described both men and women engineers as displaying a different pattern of personality traits in comparison to the college norm groups provided by Gough and Heilbrun (1980) in the manual of the Adjective Check List. According to this description, engineering students were more uncomfortable with uncertainty and were more organized.

2.3.2 Toughmindedness, Stability, and Self-sufficiency

The earliest study that could be identified that focused on the normal personality of engineers in relation to other groups revealed that engineering students were significantly more emotionally stable and self-sufficient than were liberal arts students (Goodman, 1942). The studies that used the EPPS (Izard, 1960), the PRF (Harris, 1994) and the Adjective Check List (Brown & Joslin, 1995) reported engineering students to be significantly more dominant, showing characteristics of decisiveness, toughmindedness, and straightforwardness. The engineers also had low succorance, showing more self-sufficiency than arts students. Brown and Joslin reported engineers to have a higher need for autonomy than had nursing and psychology students, and reported that they were more autonomous, assertive, determined, and stubborn, while they were less aware of self-concern and less temperamental than the members of the college norm group. In comparison to college norm samples, engineering samples scored lower on communality and femininity, and higher on dominance, self-confidence, and personal adjustment (Brown & Joslin, 1995). Similarly, based on the California Psychological Inventory (CPI; Gough, 1987), male engineering students scored higher on the scales of self-control than did a general sample of students. Finally, Kline and Lapham (1990) reported that, based on the Big Five factors, engineers and science students differed significantly from arts students by scoring higher on the factors of conventionality and toughmindedness.

2.3.3 A Preference for Cognitively-oriented Behavior

Information on the CPI (Gough, 1987) indicates that male engineering students and research scientists score higher on the scales of achievement-via-independence (i.e. clear thinking, an interest in intellectual endeavors) and intellectual efficiency (i.e.

efficient in using intellectual abilities; can keep on at a task without getting discouraged; insightful; easily expresses ideas) than do a general sample of students and the members of other occupational groups. Engineering and scientist group data were not available for women. Using the CPI and the Holland Vocational Interest Inventory, Scott and Sedlacek (1975) showed that engineers were discriminated from other students with a discriminant function labeled realistic-intellectual versus social-conventional. When either personality or interest variables were used as predictors, the two groups were placed at the opposite poles of the dimension. Engineers were found to be more realistic and intellectual compared to others.

Within the research domain of cognitive styles, Barrett and Thornton (1967) speculated that engineers would be field-independent, displaying analytical and logical characteristics, and would be capable of abstracting various aspects of a problem. Field-dependent people would either not enter engineering-related fields of study, or would be eventually screened out sometime during the educational process. A small sample (N = 46) of male employees working as engineers and technicians was compared to Witkin's standardization sample comprised of college men, based on the Rod-and-Frame test (Witkin, Lewis, & Hertzman, 1954). The authors reported that engineers were more field-independent than the standardization sample, indicating that engineers approach tasks analytically and logically by abstracting various aspects of a problem.

A large body of descriptive research on the personality of these groups has been conducted using the Myers-Briggs Type Indicator (MBTI) (Myers & McCaulley, 1985). The engineer personality norms for the MBTI were developed based on 2,389 engineering students (Myers, 1962). Myers and McCaulley (1985) reported percentages of types for engineers and for physical and life scientists. Accordingly, the most frequently appearing types for both occupational groups were the ISTJ (15.5% of engineers and 14% of scientists) and the ESTJ (12% of engineers and 9% of scientists), followed by INTJ (8% of engineers and 14% of scientists) and ENTJ (13% of engineers and 10% of scientists). Thomas, Benne, Marr, Thomas, and Hume (2000) revealed that a preference for thinking (75%) among engineers was highly distinguishable from a preference for feeling (25%), whereas preferences for the poles of the remaining dimensions were close to being equal (sensing 51%, introversion 57%, and judging 56%). Based on this result, individuals who are attracted into the engineering disciplines are, in general, analytical, objective, and dispassionate decision makers (i.e., thinking) and do not base their decisions on personal values or feelings.

2.3.4 Achievement Motivation

Based on the studies that used the EPPS (Izard, 1960), the PRF (Harris, 1994) and the Adjective Check List (Brown & Joslin, 1995), engineering students were significantly different than the general population in terms of certain personality traits. Engineers had higher achievement and endurance than did arts students, showing characteristics of being goal-oriented and energetic in that direction; had a higher need of achievement and autonomy than did nursing and psychology students; and were more ambitious and competitive. Based on the CPI (Gough, 1987), male engineering students scored higher on the achievement-via-conformance (i.e., a drive to do well, preference to work in settings where the tasks are clearly defined) and achievement-via-independence scales than did the members of a general sample of students.

2.4 An Evaluation of Literature Findings on the Personality of Engineers

In the previous section, I organized and categorized the personality correlates of engineers. A more thorough examination of the empirical studies indicated that the characteristics of the studies, such as the samples and the statistical support provided for the results, render the overall results not as conclusions but tentative suggestions pointing to some possible correlates of engineers. Investigating the personality traits of engineers needs further attention with a more comprehensive and systematic investigation. The studies outlined in the previous section were examined in terms of sample characteristics, the statistical support provided for the suggested results, and the effect sizes of the personality correlates of engineering groups. These are summarized in Appendix A.

2.4.1 Sample Characteristics and Comparison Groups

One drawback of the early studies, one which might make the results less applicable to today's engineering population, is the lack of women engineers in the vocation at the time and hence in the study samples. All studies that have been cited here that were conducted before 1970 are based on samples of men (e.g., Barrett & Thornton, 1967; Goodman, 1942; Izard, 1960). The comparison groups for these samples were also based on male populations in various other disciplines. Due to the increasing number of women in the engineering fields at the end of the 20th century, from 12% in the 1970s to 20% in 1998 (NSF, 2000), the studies conducted after the 1980s have included women in the study samples. Still, the comparisons based on the norming groups of personality inventories (e.g., Conn & Rieke, 1997; Gough, 1987) were also based on male samples.

Despite the inclusion of females in the samples, the studies conducted in the 1990s based their analyses on small engineering samples with the sample sizes ranging from 14 (Harris, 1994) to 158 (Williams, 1997) with a median of 70. Two of the studies report an equivalent gender distribution (i.e., Brown & Joslin, 1995; Williams, 1997). The majority of studies used samples of freshmen engineering or undergraduate engineering students. Two early studies and norm group samples based on the CPI and the 16PF were based on samples of employed engineers, but with small sample sizes and groups composed only of men (e.g., Barrett & Thornton, 1967; Conn & Rieke, 1997; Gough, 1987; Izard, 1960).

Most of the studies used a comparison sample with sufficient sample sizes, ranging from 166 to 1,600. The gender distribution of the comparison groups was about equal in the later studies (e.g., Brown & Joslin, 1995; Williams, 1997). Some studies used a comparison group based on the norming sample of the particular measure used. Such samples included participants from different vocational backgrounds (e.g., Brown & Joslin, 1995; Williams, 1997). The comparison groups used in other studies were more limited in nature, in that they included a sample of participants from only one or two different majors, such as a sample of arts students (e.g., Goodman, 1942; Izard, 1960; Kline & Lapham, 1990) or a sample of nurses (e.g., Harris, 1994). The restricted nature of comparison groups limits the extent to which the personality characteristics can be generalized as specific to the engineering groups.

As a result, when results of these studies are going to be considered as indicative of the engineering personality correlates, the nature of the sample and the comparison group needs to be considered. From this review it becomes apparent that there is a need for a larger sample of engineers with an increased representation of women, adequately sampled from all the different engineering specializations and compared to a variety of disciplines other than engineering, such as the social sciences, humanities, business administration, and arts. The personality inventories of 16PF and the CPI provide descriptive statistics on each scale for a variety of vocational groups. As part of this review, the engineering group norming samples were compared to the other vocational groups. Meaningful effect sizes based on Cohen's *d* and Hedges' $\hat{g}$ is provided in Appendix B and discussed under the section of effect sizes of the personality correlates.

2.4.2 Statistical Support for the Results and Calculation of Effect Sizes

Most studies identified in the literature comparing the personality traits of engineers to those of other groups were based on independent *t*-test analyses. However, none of the studies that indicated statistical differences between groups provided any effect sizes. Some of the studies even did not report descriptive results on comparison group means, standard deviations or *t*-tests that could be used in calculating the effect sizes (e.g., Brown & Joslin, 1995; Izard, 1960; Klein & Lapham, 1990).

As part of this review, effect sizes for the remaining studies (i.e., Barrett & Thornton, 1967; Goodman, 1942; Harris, 1994; Williams, 1997) are calculated based on the descriptive statistics that are reported. To calculate the size of the difference between two groups, Cohen's *d* (Cohen, 1988) is used, which is based on the difference between group means divided by the pooled standard deviation (see Equation 1).

Equation 1.

$$\text{Cohen's } d = M_1 - M_2 / \sigma_{pooled},$$

where:

$$\sigma_{pooled} = \sqrt{[(\sigma_1^2 + \sigma_2^2) / 2]}$$

In addition, as Cohen's *d* is heavily influenced by the denominator of the equation, with larger standard deviations leading to more conservative effect size estimates, Cohen's *d* is adjusted for sample sizes using the Hedges' $\hat{g}$ formula suggested by Hedges and Olkin (1985). Hedges' $\hat{g}$ (see Equation 2) adjusts for sample size by factoring sample size into the denominator to weight the standard deviations accordingly, and also adjusts the overall effect size based on the sample size.

Equation 2.

$$\text{Hedges' } \hat{g} = (M_1 - M_2) / \surd[((n_1 - 1)\sigma_1^2 + (n_2 - 1)\sigma_2^2) / (N_{total} - 2)] \times [1 - [3 / 4(n_1 + n_2)] - 9]$$

In cases where the *t* statistic was provided, Cohen's *d* and Hedges' $\hat{g}$ are calculated using the *t* value and degrees of freedom of the *t*-test based on the formulas (see Equation 3 and Equation 4) provided by Rosenthal and Rosnow (1991).

Equation 3.

$$\text{Cohen's } d = t(n_1 + n_2) / [\surd(df)\surd(n_1 n_2)]$$

Where:
$df = n_1 + n_2 - 2$

Equation 4.

$$\text{Hedges' } \hat{g} = t\surd(n_1 + n_2) / \surd(n_1 n_2)$$

Cohen (1988) defined small, medium, and large effect sizes as 0.1, 0.3, and 0.5, respectively for the evaluation of correlations, and as 0.2, 0.5, and 0.8, respectively for the evaluation of group differences based on means.

2.4.2.1 Effect Sizes of the Personality Correlates

Gough (1987) provided the means and standard deviations for a variety of vocational groups as norm data based on the 20 Folk Concept Scales of the CPI. In order to see how the personality traits of the engineering group compare to those of the other vocational groups as assessed based on the CPI, college student engineers' personality traits were compared to those of a general student sample, architecture students, students from education, students from premedical science, students from an art institute, and the students from the military academy. All participants in these samples were men. In addition, a sample of employed engineers was compared to samples of architects, bankers, business executives, correctional officers, entrepreneurs, mathematicians, military officers, police officers, research scientists, sales managers, and commercial writers. These occupational samples again were all men.

The engineering samples of both the student and occupational populations were small (student sample $N = 66$ and occupational sample $N = 47$) and there is no information in the CPI manual concerning which specific engineering areas were represented in these samples. Nevertheless, I calculated Cohen's d and Hedges' $\hat{g}$ to see how the engineering group differed from the other groups. The meaningful effect sizes for the Folk Concept Scales are reported in Appendix B for the student samples and occupational samples.

Gough (1987) categorized the 20 Folk Concept Scales into four groups. These are: 1) Measures of Poise, Self-assurance, and Interpersonal Proclivities, including dominance, capacity for status, sociability, social presence, self-acceptance, independence, and empathy; 2) Measures of Normative Orientation and Values, including responsibility, socialization (i.e., being conscientious and accepting normative rules), self-control, good impression, communality (i.e., perceiving oneself as an average person and fitting in easily, conforming), well-being, and tolerance; 3) Measures of Cognitive and Intellectual Functioning, including achievement-via-conformance, achievement-via-independence, and intellectual efficiency; and 4) Measures of Role and Personal Styles, including psychological-mindedness (i.e., insightful, understanding the feelings of others, but not necessarily supportive), flexibility, and femininity/masculinity.

According to the results, when compared to the general population, the student engineers scored higher on all the measures related to Cognitive and Intellectual Functioning, and all the measures related to Role and Personal Styles. Engineers also had higher independence scores under the measures related to Self-Assurance, and higher scores on self-control and well-being under the measures related to Values. These comparisons mostly yielded medium effect sizes ranging from .30 to .61, and a large effect size for psychological-mindedness (i.e., being insightful and perceptive, more interested in the abstract than the concrete, competent) ($\hat{g}$ = .85). When compared to education students, engineers ranked lower on all scales under the measures related to the two categories of Interpersonal Proclivities and Values, with medium effect sizes ranging from -.30 to -.68. When compared to premedical students, engineers generally ranked lower on all scales except for those in the Personal Styles category. The medium to large effect sizes ranged from -.30 to -.88. When compared to architects, engineering students in general ranked higher on the scales related to the three categories of Values, Cognitive Functioning, and Personal Styles, with effect size ranging from .44 to 1.05.

Comparisons based on the occupational groups indicated that employed engineers were systematically higher in terms of masculinity than other occupational groups representing different Holland themes, with effect sizes ranging from .46 to 2.35, and higher in terms of psychological-mindedness, with effect sizes ranging from .36 to 1.25. Research scientists, who are the investigative type, ranked higher than engineers on these scales. In terms of scales related to Cognitive Functioning, engineers were systematically higher on achievement motivation, intellectual efficiency, and tolerance than were the members of occupations pertaining to the realistic (i.e., military), social (i.e., correction officer, police officers), and enterprising themes (i.e., entrepreneurs, sales managers), with medium to large effect sizes ranging from .35 to 1.07. Engineers scored higher on socialization (i.e., rule-consciousness and conscientiousness) than did those in other occupational groups across the Holland themes, with effect sizes ranging from .42 to 1.46. Engineers did not display any other unique characteristics based on the other scales of the CPI. See Appendix B for meaningful comparisons based on the CPI.

A similar analysis was conducted on the 16PF based on the descriptive statistics for occupational groups pertaining to Holland's realistic, investigative, social, and enterprising themes provided in the *Handbook of the 16PF Questionnaire* (Cattell, Eber, & Tatsuoka, 1970). A comparison between engineers and occupations in Holland's social and enterprising themes indicated that engineers had higher levels of reasoning ($\hat{g}$ range = .41 to 1.76), rule-consciousness ($\hat{g}$ range = .40 to .94), and privateness ($\hat{g}$ range = .30 to 1.46), and lower levels of sensitivity ($\hat{g}$ range = -.58 to -2.18), apprehension ($\hat{g}$ range = -.38 to -.70), and tension ($\hat{g}$ range = -.48 to -1.07). See Appendix B for meaningful comparisons based on all 16PF variables.

In a previous section, I summarized the characteristics of various investigations that assessed personality traits of engineers based on different measures and different sample characteristics. As Appendix A shows, calculating an effect size for the difference between groups was not possible for some studies (e.g. Brown & Joslin, 1995; Harris, 1994; Izard, 1960; Klein & Lapham, 1990). The available data for the magnitude of effect unfortunately did not enable the comparison of the same personality factors across studies and measures, as only one effect size was available for one personality dimension. Despite not being able to report consistent findings, results indicate that engineers are characterized by higher scores on thinking, emotional stability, and self-sufficiency, and lower scores on interpersonally related traits such as nurturing, feeling, and agreeing. Three different studies (Brown & Joslin, 1995; Harris, 1994; Izard, 1960) reported that engineers had a consistently higher need for achievement than a general college norm sample. The CPI comparisons also yielded small to medium effect sizes for achievement-via-conformance and achievement-via-independence, respectively.

2.5 Potential Personality Correlates of the Science/Math Trait Complex

The personality correlates with sufficient information for the calculation of their effect sizes do not represent the entire set of studies that shaped the narrative review. Nevertheless, those personality characteristics that were identified to be characteristics of the engineering or science groups with moderate to large effect sizes correspond to the personality correlates identified in the personality-interest and personality-cognitive ability literature. Evaluation of effect sizes indicated that characteristics related to thinking, reasoning, openness to change, intellectual efficiency, psychological-mindedness, achievement, masculinity, self-sufficiency, self-control, emotional stability, and rule-consciousness were positive correlates, whereas sensitivity, feeling, nurturing, and agreeing were negative correlates. In the evaluation of the literature on interest-personality and personality-cognitive ability associations, openness to ideas, absorption, TIE, reasoning, thinking, rational decision making, achievement, and toughmindedness emerged as positive correlates of the science/math trait complex, and harm-avoidance, openness to feelings, warmth, and sensitivity emerged as negative correlates of the science/math trait complex.

Taken altogether, commonalities across these results indicate that traits related to "cognitively-oriented behavior," such as a tendency for thinking, reasoning, being open to ideas, and being intellectually efficient, are related characteristics of the science/math trait complex, together with traits related to "achievement" and "toughmindedness," such as masculinity, self-sufficiency, self-control, stability, rule-consciousness, low harm-avoidance, low sensitivity, low warmth, and low openness to feelings. According to Cattell et al. (1970), toughmindedness refers to being unsentimental, matter-of-fact, objective, and unaffected by feelings when appraising information and making decisions. It was found to be positively related to math and science achievement scores among middle school students (Barton, Dielman, & Cattell, 1972). Definitions of the traits that appeared as correlates based on calculation of the effect sizes are presented in Table 2.1. I propose that the above specified personality factors would be relevant both to engineers and scientists. Reynolds (1991) pointed out that the disciplines of natural sciences and engineering largely converged by the late 20th century.

Table 2.1 Potential Personality Traits Characterizing Engineering and Science Occupations

Instrument used and the study source	Personality Trait	Range of Effect Size Magnitude	Definition of Trait
NEO-PI, Carless (1999); DeFruyt & Merveilde (1997); Gottfredson et al. (1993); Sullivan & Hanson (2004)	Openness to Ideas	r = .22 to .54	Higher: Being open to new and/or unusual ideas.
16PF, Cattell, Eber, & Tatsuoka (1970); MIPS, Williams (1997)	Reasoning Thinking	$\hat{g}$ = .41 to 1.76 $\hat{g}$ = [.24]	Higher: Insightful and abstract thinking. Lower: Difficulty in starting a task.
CPI, Gough (1987)	Intellectual Efficiency	$\hat{g}$ = .35 to 1.22	Higher: Efficient in using intellectual abilities; can keep on at a task where others might give up or get discouraged; insightful and resourceful. Lower: Has a hard time getting started on cognitive tasks, and seeing them through to completion; has difficulty in expressing ideas.
CPI, Gough (1987)	Masculinity	$\hat{g}$ = [.30] to [2.35]	Masculine: Decisive, action-oriented; shows initiative; not easily subdued; unsentimental; toughminded. Feminine: Among males, seen as sensitive; among females seen as warm but also dependent.
CPI, Gough (1987)	Psychological-mindedness	$\hat{g}$ = .85 to 1.33	Higher: Insightful, perceptive, feels competent.
CPI, Gough (1987); BPI, Goodman (1942)	Self-control, Emotional Stability	$\hat{g}$ = .35 to 1.36	Higher: Tries to control emotions and temper; suppresses hostile feelings; takes pride in being self-disciplined. Lower: Has strong feelings and emotions, and makes little effort to hide them; has problems of impulsivity.
MPQ, Staggs, Larson, & Borgen (2007)	Low Harm-avoidance	r = [.19] to [.31]	Higher harm-avoidance: Tendency to avoid excitement and danger and prefer safe activities.
16PF, Cattell, Eber, & Tatsuoka (1970)	Rule-Consciousness	$\hat{g}$ = .34 to 1.47	Higher: Conscientious, conforming, moralistic, rule-bound.
16PF, Cattell, Eber, & Tatsuoka (1970); MIPS, Williams (1997)	Low Sensitivity/ Low Feeling	$\hat{g}$ = [.34] to [1.61]	Higher sensitivity: Being tender-minded, sensitive, intuitive, refined, and dependent. Lower sensitivity: Tough-minded, self-reliant, realistic, unsentimental.
NEO-PI, Sullivan & Hansen (2004)	Low Openness to Feelings	r = [.24]	Higher openness to feelings: Being concerned about own and other's feelings.
16PF, Cattell, Eber, & Tatsuoka (1970)	Low in Warmth	r = [.20] to [.45]	Higher warmth: Showing affection towards others and being concerned about how they are feeling.
MPQ, Staggs, Larson, & Borgen (2007); CPI, Gough (1987)	Achievement; Achievement-via-conformance & independence	r = .21 to .27 $\hat{g}$ = .34 to 2.14	

Note. Effect sizes are either based on comparing engineering groups with other groups or the associations between personality traits and Holland's realistic and investigative interests. r: Pearson correlation coefficient, $\hat{g}$: Hedges' $\hat{g}$ effect size for differences between groups, corrected for sample size.

CHAPTER III

VOCATIONAL INTERESTS OF ENGINEERS AND SCIENTISTS

Occupations and work environments have been classified according to the characteristics of the activities that comprise them. Holland's (1959, 1985, 1997) RIASEC interest themes provide an assessment of the individual indicating the dominant interest type and an assessment of the occupational environments based on the predominant work activities. According to the underlying principle of this framework, a person/occupation fit suggests that a person's lifestyle and his or her preferred ways of dealing with daily tasks (Holland, 1959) by and large correspond to the predominant work activities that are necessitated by the occupation in question.

According to the most recent classification of occupations under Holland's RIASEC themes (Gottfredson & Holland, 1996; Holland, 1985), engineering and science-related occupations correspond to a two-code interest theme composed of investigative and realistic interests (i.e. RI or IR). Similarly, in Strong's interest inventory (SCII, Campbell, 1974), engineering, civil engineering, mechanical engineering, and petroleum engineering occupations were among those that corresponded to the two-code Realistic-Investigative (RI) theme. Chemist, dentist, chemical engineer, electrical engineer, and geologist were among those that displayed the two-code Investigative-Realistic theme (IR). The dominant investigative theme included biologist, electronics designer, mathematician, scientific researcher, and social scientist, whereas the dominant realistic theme included skilled or semi-skilled occupations such as carpenter, electrician, farmer, forester, rancher, and skilled crafts. According to Prediger's (1982) Data/Ideas and Things/People dimensions, scientists, civil, mechanical, and electrical engineers, computer scientists, computer programmers, and workers in electronics and machine technology scored closest to the things and ideas poles. Biological scientists, chemists, and microbiologists scored closest to the ideas pole and second closest to the things pole.

3.1 Development of Engineering Interests

Studies that have focused on the development of engineering interests have indicated two themes. In the studies that can be considered historical—those conducted when the Strong Interest Inventory was developed around the 1920s—biographical experiences related to mechanical and motoric activities, such as dealing with tools and equipment, emerged as engineer interests (e.g., Beall & Bordin, 1964; Harrison, Hunt, & Jackson, 1955; Moore, 1921). Such activities that appear in early studies have shaped the nature and description of realistic interests. Researchers investigating vocational interests after the 1960s pointed not just towards mechanical activities but towards an interest in more scientific pursuits, and suggested that engineering interests show an association with achievement in science and math courses (e.g., Chaney & Owens, 1964; Mumford & Owens, 1982). With the introduction of the self-efficacy construct into the educational and vocational psychology domain in the 1980s (Hackett & Betz, 1981), researchers suggested that engineering interests developed due to the self-efficacy of the individual in the areas of mathematics and physical sciences, an efficacy which was shaped by prior exposure to such topics and achievement in them (Lent, Brown, & Hackett, 1994). The Lent et al. (1994) meta-analysis revealed an average weighted correlation of .53 between self-efficacy and interests across various domains, and self-efficacy was shown to fully mediate objectively assessed abilities and vocational interests.

Early findings indicated that attraction to engineering areas is influenced by a preference for engaging in motoric activities using tools and equipment. Scientific interests did not consistently appear in the engineering profile, and when they did, they were rated after mechanical and computational interests (e.g., Barnette, 1950; MacPhail, 1954). More recent findings indicated the role science and math efficacy played in people's attraction to engineering areas. This shift could be tied to the changing nature of engineering work due to technological advances (Duffy, 1996; Kenyon, 1993; Morgan, Reid, & Wulf, 1998; Reynolds, 1991). Before the 60s, engineering was characterized by the application of scientific principles to develop a product. Activities related to the use of tools and machines made up a large portion of the work. More recently, engineers deal with more complex data, rather than engage with tools or operations (Reynolds, 1991).

Despite mechanical interests being more pronounced in early studies, individuals who showed more favorable outcomes in engineering were the ones with higher levels of science-related interests (e.g., Barnette, 1950). Later studies (e.g., Bruch & Krieshok, 1981; Holland, 1985) that assessed interests based on the Holland typology indicated that an investigative interest was the marker in engineering areas, and such an interest was more predictive of favorable academic outcomes than were realistic interests, which are more motoric in nature.

3.2 Interests, Self-evaluations, and Vocational Outcomes

Holland (1997) posited that the congruence between an individual's vocational interests and his or her work environment would lead to greater satisfaction, performance, and persistence. Subsequent studies revealed that person-environment congruence based on Holland's typology accounts for about 5% of the variance in vocational outcomes, such as academic success, persistence, and job satisfaction, with correlations around .25 (for a review, see Spokane, Meir, & Catalano, 2000).

Studies that looked at interest-environment congruence based on Holland's themes (Bruch & Krieshok, 1981; Schaefers, Epperson, & Nauta, 1997; Southworth & Morningstar, 1970) revealed the role of interest-congruence in predicting both persistence in a chosen major and college grades. In terms of persistence, Southworth and Morningstar (1970) showed that engineering students with incongruent interest patterns, such as having higher social and artistic interests, tended to leave the major. A study by Schaefers, Epperson, and Nauta (1997) indicated that although most of the variance associated with persisting in engineering majors was due to achievement scores; interest congruence accounted for incremental prediction. Similarly, a longitudinal study among engineering majors by Leuwerke, Robbins, Sawyer, and Hovland (2004) indicated that individuals with greater interest congruence assessed based on Prediger's (1982) Data/Ideas and Things/People dimensions, persisted in the major, whereas individuals with lower congruence changed majors. Nevertheless, when interest congruence was entered into the regression equation together with ACT Math achievement scores, it did not appear as a significant predictor of retention in the engineering major.

Bruch and Krieshok (1981) tested the effectiveness of Holland's (1973) congruence method related to adjacent orientations of Investigative (I) and Realistic (R) interests in predicting academic achievement and persistence in an initial engineering major. Identical student-interest-and-curriculum congruence (e.g., I-type student in I-type engineering major) was compared to adjacent student-interest-and-curriculum congruence (e.g. R-type student in I-type major) in a college of Engineering and

Technology. The sample consisted of freshman students from electrical, mechanical and civil engineering in a college with a heavy emphasis on theoretical math/science-related curriculum. Results showed that I-type interests were more associated with persistence in these majors over a two-year period than were R-type interests. Among the students who possessed primary R interests, half of the students dropped their engineering majors over the two year period. Additional tests focusing on students who dropped engineering revealed that among R types, 65% left during the first year and 35% during the second year, whereas among I types 58% left during the first and 42% the second year. These results indicate that a higher congruence between student interest type and curriculum characteristics is important for persistence and that students who realize that they do not fit their current program tend to drop out earlier. With regard to the prediction of grade point average (GPA) among the sample, which included both persisters and non-persisters, first semester GPA was significantly different between I and R types. I types had higher GPAs than R types (Cohen's $d = 0.6$). The authors suggested that I types were more attracted to and comfortable in a theoretically-oriented engineering program due to the fact that they possessed intellectual and analytical interests, in contrast to R types, who had more manual and technical interests. A study (Sedge, 1985) that compared the career paths of engineers in the workforce also revealed the role of investigative interests. Investigative interests differentiated engineers who remained in technical-technological jobs from those engineers who made a career transition into management.

Ackerman and colleagues studied the association of interests with knowledge domains. In an adult sample of university students or graduates (Ackerman & Rolfhus, 1999), realistic interests showed a small correlation with physics knowledge ($r = .24$) and a moderate correlation with electronics knowledge (*r* = .37). Investigative interests showed moderate correlations, ranging from .33 to .35, with knowledge in chemistry, physics, technology, electronics, and astronomy. In a sample of college students and adults with at least a bachelors level of education (Ackerman, 2000), knowledge of sciences was moderately correlated with investigative interests (*r* = .41), whereas it had a significant but small correlation with realistic interests (*r* = .17).

These studies reveal that investigative interests are more associated with achievement and college persistence in science-related areas than are realistic interests. Both interest themes correlated with knowledge of sciences by .21 and .41. Nevertheless, the high drop-out rates among students with a realistic or an investigative dominant theme (Bruch & Krieshok, 1981) indicates that factors other than interests play a more influential role in predicting major persistence, or that realistic and investigative interests do not adequately reflect engineering work activities.

Self-evaluations such as self-efficacy and self-estimates of abilities have been integrated into the career literature and into interest assessments. Holland theme self-efficacy was investigated in relation to American College Testing (ACT) scores and college GPA in a general sample of college students (*N* = 313) (Lindley & Borgen, 2002). Investigative theme self-efficacy significantly correlated with ACT scores (*r* = .32 for men, *r* = .38 for women) and GPA (*r* = .17 for women, *r* = .19 for men), whereas realistic theme self-efficacy significantly correlated with ACT scores (*r* = .19) only, among women. For both men and women investigative theme self-efficacy significantly predicted GPA (β = .30 for women and β = .25 for men) and ACT scores (β = .38 for females and β = .40 for males). Realistic theme self-efficacy did not predict ACT scores.

For both sexes realistic interests predicted GPA (females $\beta = -.21$, males $\beta = -.21$), but the direction of the relationship was negative.

The study of Lent, Brown, and Larkin (1987) indicated that self-efficacy and vocational interests significantly predicted academic grades, persistence, and perceived career options. Self-efficacy for the educational requirements and academic milestones related to the science and engineering majors, and interest congruence assessed with the SCII General Occupational Themes, together predicted perceived career options, with an incremental variance of 16% over cognitive abilities. Self-efficacy had significant unique predictive variance over abilities in predicting science and technical course grades, college persistence, and perceived career options, with an incremental variance ranging from 7% to 11%. However, self-efficacy and interest congruence did not add incremental variance over one another in the prediction of these outcomes. A similar study by Schaefers, Epperson, and Nauta (1997) revealed that science and math self-efficacy, interest congruence, and perceived support and barriers significantly predicted persistence in an engineering major, after controlling for the significant effect of academic achievement. A model with all four variables correctly identified 92.6% of persisters and 62.3% of non-persisters. A study by Siegel, Galassi, and Ware (1985) revealed that in the prediction of mathematics course grades of undergraduates, the level of math self-efficacy added significant incremental variance over the average of previous exam grades with a 1% increase in variance, and in a separate analysis added significant incremental variance over SAT Math scores, with a 13% increase in explained variance.

Ackerman and Rolfhus (1999) studied self-concept and self-estimates of abilities in relation to domain knowledge. Magnitude of significant correlations of self-concept and self-estimates of abilities in mathematics and the spatial domain with knowledge in biology, chemistry, physics, astronomy, electronics, economy, technology, and tools ranged from .21 to .55. In a general investigation of interests and ability self-estimates in relation to occupational choice, based on a sample of 4,679 grade 12 students, Tracey and Hopkins (2001) showed that interests assessed based on Prediger's dimensions and ability self-estimates together accounted for 31% of the variance in occupational choice. Although interests explained a higher percentage of variance (27%), ability estimates by themselves explained a significant portion of variance (18%). Interests assessed with the UNIACT showed higher hit rates for classification of criterion groups (64%) than did ability self-estimates assessed with the Inventory of Work Relevant Abilities (58%) in a sample of college students (Prediger & Brandt, 1991).

Self-evaluations based on Holland themes correlated with outcomes (e.g. achievement) ranging from .17 to .40, which is similar to the range of interest-achievement correlations. Domain specific self-evaluations showed a somewhat higher range of correlations, from .21 to .55 with achievement (i.e. domain knowledge) than did Holland theme self-efficacy. In general, interest assessment based on Holland's themes resulted in higher correct classification of criterion groups (Prediger & Brandt, 1991) and explained a higher percentage of variance in occupational choice (Tracey & Hopkins, 2001) than did ability self-estimates.

The present review has highlighted some points that are indicative of the inadequacy, in terms of predicting vocational outcomes, of the two interest themes in the assessment of engineering and scientist interests. The aforementioned findings indicate that realistic interests and related self-efficacy beliefs are not strong predictors of academic outcomes in the engineering majors. Such majors require high levels of cognitive abilities (Gottfredson, 1986). Although realistic interests have a moderate correlation with spatial abilities ($r = .34$) and significant small correlations with form perception ($r = .13$) (Randahl, 1991) and with numerical abilities ($r = .16$ for females) (Careless, 1999; Randahl, 1991), realistic interests do not show significant correlations with general abilities (Careless, 1999). Realistic interests were also found to be weakly correlated ($r = .17$) with science domain knowledge (Ackerman, 2000), though higher correlations were observed with domain-specific knowledge, such as electronics ($r = .37$) (Ackerman & Rolfhus, 1999). All these findings indicate that realistic interests are correlated with specific outcomes such as domain-specific knowledge, but are insufficient to predict vocational outcomes such as persisting in an engineering or science-related major.

Investigative interests appear to be more associated with achievement and with persistence in engineering- and science-related areas than are realistic interests. Investigative interests are moderately correlated with knowledge in sciences ($r = .41$) (Ackerman, 2000). Although investigative interests also show a small correlation with numerical abilities ($r = .16$ for females and $r = .10$ for males) (Careless, 1999) they are more highly correlated with general cognitive abilities ($r = .33$ for females and $r = .40$ for males) than are realistic interests. Although investigative interests do a better job predicting achievement and persistence than do realistic interests, study findings (Bruch & Krieshok, 1981) indicated that approximately 50% of students with investigative interests left their interest-congruent majors. I argue that interest assessments could be improved to be more predictive of a person's fit in such higher-ranked vocational areas.

3.3 Assessing Interests for Vertically Aligned Work Environments

In this section I outline the necessity to develop an assessment of interests for vertically aligned work environments and describe the occupational classifications and theoretical frameworks used to build such an assessment.

3.3.1 The Need to Develop an Interest Assessment for STEM Areas

Currently, the related activities sampled in interest inventories corresponding to the Science, Technology, Engineering, and Math (STEM) areas do indicate a direction of interest towards domains related to such occupations. However, the content subsumed under the interest themes does not seem to adequately tap into cognitively complex tasks that require a high level of intellectual ability. For example, an item from the realistic theme in the UNIACT Interest Inventory (Swaney, 1995) is “Design a bird feeder,” one from the O*NET Career Exploration is “Assemble electronic parts” (O*NET, 2006), and one from the Self-Directed Search Form-R (SDS; Holland, 1994) is “Repair cars.” In terms of face validity, such items do not indicate a preference for engaging in cognitively more complex tasks that would correspond to STEM occupations. The realistic domain assesses motoric interests that can be a part of a variety of occupations either with lower-ability demands or with higher-ability demands. However, realistic interest assessments do not provide an adequate assessment of items that directly relate to more complex tasks pertaining to engineering activities, such as designing electro-mechanical equipment, designing chips, using computer graphics design software, or application of mathematics or statistics to solve problems.

Similarly, although Holland’s investigative theme is related to intellectual abilities (e.g., Careless, 1999), not all items sampled in the inventories necessarily reflect a higher demand on cognitive abilities. For example, an item from the UNIACT (Swaney, 1995) assessment that measures investigative interests is, “I’m interested in learning about star formations,” one from the O*NET assessment is, “Study the structure of the human body” (O*NET, 2006), and one from the SDS (Holland, 1994) is “Read scientific books or magazines.” Some items in Holland’s SDS (Holland, 1994) do tap into cognitively more demanding work (e.g., “Take a Physics course”), whereas most items do not. These items are ambiguous in terms of the level of cognitive demand required to accomplish the tasks described. For example, an individual who reports an interest in learning about star formations can be interested in narrative magazine article reviews of star formations that would not entail much cognitive demand, but not in putting effort into studying the underlying physical principles and formulas.

To be more specific, a person with a lower-complexity level of interest may only want to read the following paragraph from a narrative article in Universe Today (2010):

> “A star is formed out of cloud of cool, dense molecular gas. In order for it to become a potential star, the cloud needs to collapse and increase in density.”

Another person with a higher-complexity level of interest may be eager to deal with cognitively more demanding tasks, like using physics and chemistry formulas in explaining the formation, such as the “gas-density power law” expressed in terms of the observable surface densities of gas and star formation: $\sum SFR\backslash A \sum^{N}{}_{gas}$ (Kennicutt, 1998).

Even though there is direction of interest, stating an interest in some of these items may not indicate a readiness to pursue such domains at the college or occupational level, where engagement with the content is cognitively demanding and complex. There is a need to integrate a dimension in interest inventories that would capture what level of occupation an individual would be interested in pursuing. Although self-evaluations (e.g. self-efficacy and ability self-estimates) have been integrated into career assessments, an assessment of the level of complexity one is interested in may, for several reasons, add incremental variance over interests and self-evaluations in the prediction of vocational outcomes. Self-evaluations related to the realistic, and to a greater extent, to the investigative themes also predict achievement and persistence (e.g., Lent et al., 1987; Lindley & Borgen, 2002). However, the magnitudes of correlations are in the moderate range, around .30. In addition, a meta-analysis suggested that self-efficacy was more strongly correlated with work-related performance when the job or task was low rather than high in complexity; a weaker correlation was found in those jobs that are coded as complex in terms of their required knowledge, skill, and abilities by the Occupational Information Network (Judge, Jackson, Shaw, Scott, & Rich, 2007). Thus, self-efficacy assessments may not substitute for indicating an interest in getting involved in cognitively complex occupations.

Finally, even though self-evaluations have been shown to add incremental variance in vocational outcomes over cognitive abilities, interest congruence and self-efficacy were not found to add incremental variance over each other in the prediction of grades, persistence, and perceived career options (Lent et al., 1987). Ability self-estimates were shown to be poorer in predicting hit rates for correctly classifying vocational criterion groups than was assessing interests. With a sample of 2,915 seniors from various vocational-technical schools, Prediger and Brandt (1991) showed that interests had a 64% hit rate and ability self-estimates had a 58% hit rate.

3.3.2 Occupational Classification Systems

Assessing interests along a complexity dimension necessitates reviewing how occupations are classified. Since 1939, the U.S. Employment Service (USES) has produced databases that describe and classify jobs to be used in employment services. Among USES service products are the Dictionary of Occupational Titles (DOT; U.S. Department of Labor, 1991), the Guide for Occupational Exploration and the Occupational Aptitude Pattern Structure (U.S. Department of Labor, 1979). Occupations have been classified based on their work characteristics and ability requirements.

3.3.2.1 The Dictionary of Occupational Titles (DOT)

The Dictionary of Occupational Titles (DOT; U.S. Department of Labor, 1991) provides descriptions of work activities for more than 12,000 job titles which have been rated for worker functions, physical demands, environmental working conditions, training times, required aptitudes, temperaments, interests, required math level, and required language level. Ratings on these dimensions make up the 9-digit classification code of occupational titles. Worker function ratings are based on complexity of dealing with data, people, and things as indicated by the forth, fifth, and sixth digits of the code. The final version of DOT was published in 1991.

3.3.2.2 Guide for Occupational Exploration (GOE)

Further classification of job descriptions found in the DOT is achieved through the Guide for Occupational Exploration (U.S. Department of Labor, 1979), which classifies occupations based on similarities in job attributes. It classifies the occupations listed in the DOT into 66 Work Groups based on a rational approach, in which all occupations listed under the DOT were first classified into 12 vocational interest areas identified and then further classified into more homogeneous groups based on tasks, work conditions, interests, temperaments, and aptitude requirements. Occupational Aptitude Patterns (OAP) based on the Specific Aptitude Test Battery profiles of occupations and DOT aptitude ratings were developed to represent each of the 66 GOE Work Groups, covering more than ten thousand job titles.

3.3.2.3 Occupational Information Network (O*NET)

The Occupational Information Network (O*NET, 2006) is an online database that classifies jobs into job families. It provides information about the work activities performed and the required applicant qualifications for each occupation. A total of 812 occupations are classified under the O*NET Standard Occupational Classification taxonomy, which defines sets of occupations across the world of work.

3.3.3 Occupational Level and Complexity

When Holland proposed his theory of vocational choice in 1959, he specified occupational environments (the RIASEC typology), and also incorporated the notion of occupational level into his theory (Holland, 1959). Within a given class of occupational environments, the intelligence and self-evaluations of the individual were the factors determining the “level” of choice. In this theory, occupational level was synonymous with the status of a particular occupation in the occupational class, or the status of the position the individual holds in the occupation. The theory posited that the occupational level that would fit an individual could be predicted by his or her level of objectively-assessed intelligence plus his or her level of self-evaluations, which covered his or her need for status, perceived level of confidence, potential confidence, and personal worth relative to others. The ordering of occupational levels across individuals based on this estimation was referred to as the “level hierarchy of occupations.” This means, for example, an occupation at the highest level would fit an individual with the highest level of intelligence and the highest level of self-evaluation. Although Holland suggested the personal determinants of “occupational level,” he did not provide a sufficient definition or specifications as to the concept of “level” or “status”.

Gottfredson (1980) argued that a scheme that incorporates level distinctions into the Holland typology would predict variance in job characteristics better than the six-category typology, and that occupational classification needs to be supplemented by distinctions in job level. Gottfredson (1986) extended Holland’s theory and adopted an ability-based classification of occupations, which integrated the minimal level of general ability and specific abilities required by an occupational group. Gottfredson classified the 66 Occupational Aptitude Patterns of GOE Work Groups into 13 clusters based on the major work activities and the minimal level of the most important aptitudes that the work requires. The 13 clusters form four broader clusters of general functional work areas related to dealing with “physical relations,” “maintaining bureaucratic order,” “social and economic relations,” and “performing.” Within each area of work, occupational clusters are ordered vertically according to the required general intellectual difficulty level and prestige level, which make up the level of complexity, with ratings ranging from 1 to 10. For each occupation in the clusters, the minimal level (i.e., cutting points) of general ability and relevant specific abilities (e.g., verbal, numerical, spatial, perceptual, psychomotor abilities) are indicated. The cutting points were determined in a way such that the proportion of workers in an occupation who exceeded the cutting points on all relevant abilities also met work-related criteria (e.g. supervisory performance ratings) at a satisfactory level.

STEM occupations are located in the "physical relations" functional work area of the OAP map (Gottfredson, 1986), referred to as "P." This area includes clusters P1 through P5, in which workers deal with physical systems, either mechanical or biological. The first cluster "P1," is related to researching, designing, and modifying physical systems, and includes occupations like engineering and sciences. Two characteristics of this P1 cluster are that it is ranked highest under all physical relations clusters in terms of the job complexity level (with a rating of 10 out of 10) and in terms of the minimum level of required cognitive abilities (Gottfredson, 1986). The other clusters were identified in terms of decreasing level of complexity, as follows: the P2 cluster of "operating and testing physical systems" (e.g., plant manager, complex vehicle operators, drafter, lab technician and technologist), the P3 cluster of "crafting or inspecting complex objects, repairing, operating, or setting up equipment or vehicles" (e.g., carpenter, truck driver, bridge inspector), the P4 cluster of "crafting, finishing, assembling, sorting, or inspecting simple objects" (e.g., tire inspector, glass cutter, garment sorter), and the P5 cluster of "tending (machines, buildings, plants, animals) and attending (workers, the public)" related to semiskilled or unskilled manual work (e.g., general laborer, baker's helper). The P1 cluster occupations require a minimum general intelligence level of 115, a verbal ability level of 105, and numerical and spatial ability levels of 110. The required general intelligence level of 115 is 0.75 standard deviation above the population mean. The P2 cluster of technological occupations require a minimum general intelligence level of 105, and minimum verbal, numerical, and spatial ability levels of 100. The remaining P clusters have been ordered rationally and no information as to the minimum level of required intelligence for the P3, P4, and P5 clusters was available.

A comparison of the P1 and P2 clusters with ratings of DOT Worker Functions in terms of the complexity of the work dealing with data, people, and things revealed that the P1 and the P2 clusters were characterized by a very high complexity of dealing with data (means are 0.4 and 0.6, where 0 = high complexity and 6 = low complexity), a high level of complexity with dealing with things (means are 2.4 and 3.8, where 0 = high complexity, 7 = low complexity), and a low level of complexity with dealing with people (means are 4.9 and 6.2, where 0 = high complexity, 7 = low complexity). All of the first four "P" clusters are characterized by a high complexity level of dealing with things.

Gottfredson (1986) reported that the P1 and P2 clusters span both the realistic (14% of P1 and 39% of P2 occupations) and investigative themes (39% of P1 and 32% of P2 occupations), while the P3, P4, and P5 clusters span only the realistic theme. The Dictionary of Holland Occupational Codes (Gottfredson & Holland, 1996) lists the occupations within each three-letter Holland category in descending order of level of complexity. The estimated complexity level of these occupations ranges from 40 to 80. It is possible to arbitrarily divide this range into three— below 55, 55-69, and 70-80—to indicate occupations with low, moderate, and high levels of complexity. In Appendix C some examples of the occupations, under the RI and IR categories, that correspond to each of these levels are presented together with their estimated level of complexity and their corresponding codes from the Dictionary of Occupational Titles (DOT). Under the RI code, engineering occupations are generally found at the higher occupational complexity levels, with estimates ranging from 66 to 77. Under the IR code, engineering occupations are found between estimates of 70 and 80. Under these codes, moderate and low levels correspond to occupations of technologists, technicians, laboratory or medical assistants, operators, assemblers, repairers, and laborers.

At this point it is important to distinguish between the various conceptualizations of occupational level. A study by Spaeth (1979) showed that, based on the role and activities of occupational incumbents, "vertical occupational differentiation" had three dimensions: authority, prestige, and complexity. Spaeth noted that "authority" referred to administrative authority and economic control. Indicators for authority were defined as the degree of involvement with people, work in supervisory roles, and independence from other authority figures. "Prestige" referred to perceptions of the general public and its indicators were defined as educational level and occupational income level. "Occupational complexity" referred to a continuum, with routine jobs consisting of simple, repetitive tasks at one end and professional occupations characterized by highly complex work in a narrowly defined field at the other end. Indicators for complexity were defined as the rated complexity of work with data, general educational development, and vocational preparation, all based on the DOT. This review focuses on the occupational complexity dimension of occupational level.

3.3.4 Components of Occupational Complexity and Interest Complexity

The degree of involvement of the work activities with data, things, and people is the basis for rating the complexity of occupations in the DOT. Nevertheless, as Spaeth (1979) suggested, the degree of involvement with people is related to ordering occupations on the authority dimension. Thus, the level of involvement with data and things is relevant to the occupational hierarchy that reflects occupational complexity. However, involvement with things does not vary much across the occupations in the P cluster. Mean ratings of level of involvement with things across the five levels of “physical” cluster occupations have a range of three out of a possible range of seven points (Gottfredson, 1986). Therefore, for the purposes of this review on STEM-related vocational tracks, involvement with data is the most relevant component for determining complexity levels.

The complexity level of involvement with data is expressed as the 4th digit of the DOT code number, and is rated on a 7-point scale, from 0 to 6. The scale points starting with the most complex involvement with data are: 0 = synthesizing, 1 = coordinating, 2 = analyzing, 3 = compiling, 4 = computing, 5 = copying, and 6 = comparing. An upper-level task includes all the lower-levels tasks. The occupations classified under the RI theme in the DOT vary a great deal on the basis of the degree of involvement with data, covering all levels of involvement with data. The mean ratings of involvement with data have a range of 5.5 out of a possible range of six points (Gottfredson, 1986).

What the DOT does not cover is a level of involvement with *ideas*. According to Prediger’s (1982) theory, there are two dimensions that underlie Holland’s hexagonal model of vocational environments. One dimension indicates a high degree of involvement with things at one end, corresponding to the realistic theme, and a high degree of involvement with people at the other end, corresponding to the social theme. The other dimension indicates a high degree of involvement with data at one end, corresponding to the conventional theme, and a high degree of involvement with ideas at the other end, corresponding to the investigative and artistic themes. Although in the

DOT, Holland's vocational environments and the corresponding occupations are ordered in terms of occupational complexity based on the degree of involvement with data, things, and people, the component of involvement with ideas has not been integrated. Involvement with data can involve ideas, when engaging in synthesizing, analyzing, or even comparing at the lowest level. Nevertheless, involvement with ideas does not necessarily depend on interacting with numerical or verbal data, but goes further in drawing inferences from data, reasoning about propositions, linking data results with previous knowledge, engaging in theoretical thought, generating new theories, and so on. A component of involvement with ideas together with data would be relevant in terms of ordering occupations according to their complexity level.

At this point, the forms of involvement with data need to be considered. Data can be in numerical format, verbal format, symbolic notational/abstract format, or spatial/ graphical format. This study's focus will be on interests in dealing with data that have increasingly complex numeric, symbolic, and spatial forms of information, and on interests in dealing with increasingly complex forms of interaction with ideas. The ideas domain by definition includes verbal content with which to interact. Such a conceptualization of occupational complexity seems especially relevant for the RI and IR themes, encompassing the STEM occupations.

3.3.5 Associates of Interest Complexity

Assessing one's level of interest complexity means assessing the desire of an individual to work on tasks and activities characteristic of differing levels of occupational complexity, tasks which vary in their cognitive demands. For example, according to the DOT, the work of a research scientist is ranked very high in terms of occupational complexity. A person who would fit this occupation and be satisfied in it would be expected to display a desire to work in a cognitively complex environment that demands high intellectual abilities and a willingness to work hard in order to be competent and to remain at such a level of complexity. The work of a laboratory technician is ranked lower in the DOT, with a lower level of occupational complexity. A person who would fit this occupational level, be satisfied, and remain in the occupation would be one with a desire to engage in more moderate levels of cognitively complex work. I argue that an individual's desire to engage in increasingly complex tasks, tasks which are cognitively more demanding, would be associated with that individual's cognitive abilities, a dispositional tendency to engage in intellectual activities, and learning goals as a motivational process to engage in complex tasks.

3.3.5.1 Cognitive Abilities

As identified by Gottfredson (1986) the P1 cluster, including STEM occupations, requires a high complexity of dealing with data, a high levels of general intelligence, and numerical, spatial, and verbal abilities. The estimated levels of required abilities for the P1 cluster are higher than any other occupational cluster. The P2 cluster followes the P1 cluster in the required level of abilities. Although verbal ability was not a correlate of Ackerman's (2000) science/math trait complex, the intellectual/cultural trait complex characterized by verbal abilities was also significantly correlated with knowledge in physical sciences. In a sample composed of college students and adults who had at least a bachelor's degree, a correlation of .40, and in another sample of college students a correlation of about .25, was reported between the intellectual/cultural trait complex and knowledge in physical sciences (Ackerman, 2003). These results suggest that numerical, spatial, and verbal abilities are associated with performing in STEM-related areas. These abilities are expected to be correlates of a desire to engage in cognitively complex tasks.

3.3.5.2 Intelligence as Typical Performance

Goff and Ackerman (1992) proposed Typical Intellectual Engagement (TIE) as a dispositional construct associated with intelligence as *typical* performance as opposed to *maximal* performance, which was supported by TIE's differential association with fluid and crystallized intelligences (Horn & Cattell, 1966). Fluid intelligence, which is viewed as physiologically based and associated with general reasoning abilities involving figural and nonverbal content, was not correlated with TIE (r = -.06), whereas crystallized intelligence, which is viewed as the experiential aspect of intelligence associated with the application of verbal and conceptual knowledge, was significantly correlated with TIE (r = .22).

TIE has been defined as the expression of "a desire to engage and understand the world, interest in a wide variety of things, and a preference for a complete understanding of a complex topic or problem, a need to know" (Goff & Ackerman, 1992, p.539). Analysis of the construct's nomological network (Goff & Ackerman, 1992; Rolfhus & Ackerman, 1996) suggested that TIE was substantially related to hard work, absorption, extroverted intellectual engagement, introverted intellectual engagement, the FFM openness to experience factor, an interest in the arts and humanities, and an interest in social sciences (r range = .55 to .73); moderately related to perfectionism, lack of distractibility, an interest in science, and knowledge in humanities and art (r range = .31 to .49); and somewhat related to ACT English, Reading, Science Reasoning, and composite scores, and the FFM conscientiousness factor (r range = .17 to .28). TIE was also significantly correlated with knowledge in physical sciences (*r* = .29) (Ackerman et al., 2001). It was highly associated with need for cognition proposed by Cacioppo and Petty (1982), which refers to a motivational process to seek and enjoy effortful cognitive activities. The association between TIE and need for cognition was reported to be .78 (Woo, Harms, & Kuncel, 2007). TIE is related to an individual's desire to engage in cognitively complex work, hence is suggested as a correlate of interest complexity.

3.3.5.3 Goal Orientation

In addition to cognitive abilities, I argue that there is a motivational component indicative of an individual's level of interest complexity. I argue that the level of motivation to engage in complex tasks is also a function of goal orientations.

Individuals with a learning goal orientation (Dweck & Leggett, 1988) believe in the controllability of their intellectual abilities, exert further effort in learning a task, find hard tasks challenging, and persist in times of failure. The other type of goal orientation is performance goal orientation (Dweck & Leggett, 1988), which is defined as a tendency to think that abilities cannot be improved, a belief that exerting effort will not lead to returns, and in times of failure, a tendency to lose interest in the task and withdraw. Such individuals strive only to demonstrate competence in order to gain favorable outcomes and try to avoid negative judgments.

A meta-analytic investigation of the nomological network of goal orientations (Payne, Youngcourt, & Beaubien, 2007) suggested how learning goal orientation (LGO), performance-prove goal orientation (PPGO), and performance-avoid goal orientation (PAGO) were differentially related to antecedents, proximal consequences, and distal consequences. Antecedents of LGO were general self-efficacy, need for achievement, openness to experience, self-esteem, extraversion, conscientiousness, and a belief that intelligence is malleable ($\hat{\rho}$ range = .12 to .71). PPGO was negatively associated with emotional stability ($\hat{\rho}$ = -.32) and self-esteem ($\hat{\rho}$ = -.11), and was not associated with the need for achievement or any of the personality factors. PAGO was associated with a belief that intelligence is not malleable ($\hat{\rho}$ = .09) and was negatively associated with need for achievement, emotional stability, openness to experience, conscientiousness, self-esteem, and general self-efficacy ($|\hat{\rho}|$ range = -.15 to -. 61). In terms of outcomes, LGO was positively associated with task specific self-efficacy, learning strategies, feedback seeking, learning and academic performance, and job performance ($\hat{\rho}$ range = .16 to .49). PPGO had small associations with learning strategies ($\hat{\rho}$ = .16) and job performance ($\hat{\rho}$ = .11), and was unrelated to task-specific self-efficacy, feedback seeking, learning, or academic performance. PAGO was associated with state anxiety ($\hat{\rho}$ = .36), and inversely with task specific self-efficacy, feedback seeking, and learning ($\hat{\rho}$ range = -.17 to -.26). Finally, meta-analysis showed that LGO added significant incremental validity over cognitive abilities and the personality variables in predicting job performance, whereas PPGO or PAGO did not.

The characteristics of individuals with an LGO, such as displaying a need to achieve, a belief that abilities could be improved, an openness to intellectual pursuits, a propensity for hard work and conscientiousness, and higher levels of self-efficacy, could suggest that such individuals may seek cognitively challenging contexts and work towards achieving in such contexts. Specific associations indicated that individuals with an LGO either seek challenge or show adaptive responses in challenging situations. In a sample of high school students, those with an LGO reported enjoying the challenge (*r* =

.34) (Ames & Archer, 1988). Grant and Dweck (2003) showed that, in a sample of college community individuals, those with an LGO (which is operationalized as a learning and challenge-mastery orientation) responded adaptively to failure by making effort based attributions and persisting (i.e., engaging in planning, active coping, inverse associations with loss of intrinsic motivation, withdrawal of time and energy, behavioral and mental disengagement, with magnitude of Beta coefficients ranging from .28 to .57). Members of a sample of freshman college students with an LGO showed improvements in their grades over the semester in a chemistry course ($\beta = .25$) (Grant & Dweck, 2003). Finally, it was found that undergraduate students with a higher LGO set higher goals in more difficult classes than individuals with a lower LGO (coefficient of interaction = .50) (Horvath, Herleman, & McKie, 2006).

One could assume that the more cognitively complex and demanding a task is, the more challenging it would be for most individuals, and the more it would require motivated work and persistence. An individual with higher LGO could be expected to show a higher interest in cognitively complex tasks because they seek challenge and respond to it adaptively, and an individual with a lower LGO could be expected to show a lower interest in more complex tasks.

CHAPTER IV

THE PRESENT STUDY

In the present study, I seek to delineate the non-ability correlates (i.e. personality and interests) of the science/math trait complex. The first objective of the study is to identify personality correlates of the trait complex. The second purpose is to revisit the STEM-related interests by introducing a new assessment referred to as STEM Interest Complexity, which is hypothesized to add incremental variance over traditional interest assessments in predicting vocational criteria.

4.1 Identifying Science/Math Trait Complex Personality Correlates

The first objective of the study is to identify personality correlates of the science/math trait complex. With this purpose in mind, I reviewed the literature on cognitive ability-personality and interest-personality relations. Following this, I reviewed the personality correlates of engineering and sciences. Taken together, support was found for the personality traits related to openness to ideas, reasoning, intellectual efficiency, thinking, psychological-mindedness, achievement, masculinity, rule-consciousness, self-control, self-sufficiency, low sensitivity, low harm-avoidance, low warmth, and low openness to feelings.

Statistical support could not be provided to show that these results converged across studies that investigated engineering personality. I noted that most of the studies were based on samples mostly composed of only male participants. Studies in general compared an engineering sample to one other vocational group, such as a group of nurses, a group of psychology students, or a group of arts students. Thus, the aforementioned personality factors need to be further supported with a more systematic investigation of the scientist and engineering personalities. The present study aimed to investigate the aforementioned constructs, with a sample of STEM major students composed of men and women, and adequately represented by different engineering and science areas, to be compared with a variety of other vocational groups that span across Holland's vocational environments. Hence, the main focus of Study 1 was testing the personality traits hypothesized to be characteristic of individuals in STEM areas. Another aim of Study 1 was to focus on preliminary item and scale level analyses of the newly developed STEM Interest Complexity Measure, assessing interests in different levels of cognitively complex tasks. Validation of this new measure is the focus of Study 2. How the measure was developed is described below.

4.2 Assessment of Interests in Cognitively Complex Tasks

There is a need for an interest assessment, which reflects the higher-complexity STEM-related work activities by differentiating them from the lower-complexity technical, skilled and semi-skilled occupations represented under the realistic and investigative themes. I propose that this differentiation could be achieved by integrating a vertical dimension into vocational assessment. This integrated approach of assessing both direction of interests and a preference for cognitively complex tasks may provide a more representative and valid assessment of an individual's vocational choice and likely fit into the STEM fields, as compared to only assessing the direction of interests. The focus of Study 2 was the construct and criterion-related validation of the new measure. More detailed descriptions of Study 1 and Study 2 are presented in Chapter 5 and Chapter 8, respectively, focusing on the study hypotheses and method.

The career outcomes as identified by Gottfredson (1996) are satisfaction, performance, persistence, economic stability, and identity. Vocational interests have been shown to predict satisfaction, performance, and persistence in the academic arena. Person-environment and interest-occupation congruence have been shown to be associated with success at the higher education level (e.g., Tracey & Robbins, 2006) and occupational level (e.g., Kristof-Brown, Zimmerman, & Johnson, 2005).

Tracey and Robbins (2006) showed that at the higher education level, students who had an interest profile similar to the characteristics of the major they were enrolled in had higher GPAs in their first year, second year, and at the time of graduation. Interest congruence added 4-5% incremental variance over ACT scores in the prediction of grades. Similarly, interest congruence was predictive of persistence in a major. Beyond college education, the concept of "fit" has also been shown to be an important predictor of various organizational outcomes. The recent meta-analytic study of Kristof-Brown et al., (2005), which examined organizational outcomes related to the fit of personal characteristics to the job, organization, group, and supervisor, revealed the importance of fit in the work domain. Person-job fit is similar to the notion of person-vocation fit which refers to the match between an individual's interests and the characteristics of a career domain. Person-job fit assessed as a combined measure of "the fit between individual needs and job supplies" and "the fit between job demands and individual abilities" was strongly related to job satisfaction ($\hat{\rho} = .62$), organizational commitment ($\hat{\rho} = .51$), and intentions to quit ($\hat{\rho} = -.57$). Compared to fit to the organization, group, or supervisor, job fit was found to be most strongly related to job satisfaction, intentions to quit, and tenure (Kristof-Brown et al., 2005).

If interests are associated with outcomes throughout an individual's career path, from college major selection to persistence and occupational attainment, then it is also important to assess interests that would be most reflective of the requirements of the specific vocational field. The current vocational assessment systems are based on assessing interests towards characteristics of work environments based on Holland's hexagonal model with six themes (Holland, 1985, 1997) and related Basic Interest Scales or self-efficacy scales. In the present study, I argue that such systems do not differentiate people who would fit more complex occupations from those who would fit less complex occupations, along the vertical alignment of occupations (Gottfredson, 1980, 1986; Spaeth, 1979). For example, determining that a person has a two-code dominant interest theme that fits the Realistic-Investigative (RI) work environment does not provide any further information as to whether that person would be more satisfied in a highly-complex occupation, such as electronics engineering, or a less-complex occupation, such as that of an electro-mechanical technician. These occupations involve tasks with varying levels of complexity, but both are under the RI theme. Meta-analytic evidence indicated that self-efficacy was more strongly correlated with work-related performance when the job or task was low in complexity compared to when it is high in complexity (Judge et al., 2007). Thus, self-efficacy assessments may not substitute for indicating an interest in getting involved in cognitively complex occupations.

This study focuses on the development of an instrument to assess individuals' interest and desire to engage in different levels of cognitively complex tasks. The aim is to add incremental predictive validity to already existing interest assessment systems in the prediction of vocational outcomes such as satisfaction, performance, and persistence.

4.2.1 Development of the STEM Interest Complexity Scales

I developed the STEM Interest Complexity Measure to assess individuals' interests in varying levels of cognitively complex tasks (to be referred to as "interest complexity"). This study is geared toward the vocational areas related to the realistic and investigative themes. Therefore the focus of the content domains are those typical of tasks in these areas. More specifically, the STEM Interest Complexity scales are based on a preference for dealing with data in the content domains of "numerical information," "symbolic/abstract information," "spatial/graphical information," and on a preference for dealing with "ideas" at differing levels of complexity. A more-complex task is defined as one which includes elements from lower-level tasks as well as additional elements. In addition to assessing complexity in the relevant domains, I developed a scale geared towards assessing complexity of interests for more general tasks in STEM related areas.

The guidelines followed in the development of the domain scales were two-fold: (1) Identifying the complexity levels of occupations under the RI and IR themes, and the dimensions used in ranking the occupations in terms of complexity; and (2) Identifying how the skills, abilities, and work activities differ in different complexity occupations.

4.2.1.1 Identifying Ocupational Complexity

As an initial step, the occupations listed under Holland's RI and IR themes were identified using the Dictionary of Holland Occupational Codes (Gottfredson & Holland, 1996). Gottfredson (1986) provided a vertical classification of such occupations based on their job complexity (JC) levels, rated on a 10-point scale, and their cognitive ability requirements. The RI and IR occupations were identified as the “P” domain, which included occupations dealing with physical relations. Based on JC, this domain was classified into five clusters: P1) Researching, designing, and modifying physical systems (chemist, physician, engineer), with a JC rating of 10; P2) Operating and testing physical systems (plant manager, drafter, lab technician) with a JC rating of 8; P3) Crafting or inspecting complex objects: repairing, operating, or setting up equipment or vehicles (carpenter, truck driver, bridge inspector) with a JC rating of 5; P4) Crafting, finishing, assembling, sorting, or inspecting simple objects (tire inspector, glass cutter, garment sorter) with a JC rating of 2; and P5) Tending (machines, buildings, plants, animals) and attending (workers, public) (yarn sorter, general laborer, baker’s helper) with a JC rating of 1.

Occupations under the RI and IR themes were also examined in terms of the occupational complexity levels as identified by the Dictionary of Occupational Titles (DOT; U.S. Department of Labor, 1991), in which the worker function ratings are based on complexity of dealing with data, people, and things. As discussed in the section entitled “Components of Interest Complexity,” I decided to develop items for the interest complexity measure based on the complexity of involvement with numerical data, symbolic/abstract data, and spatial data domains. In addition, I added items based on complexity of involvement with ideas.

Where possible, the levels of complexity for items developed in the scales of involvement with numerical data, symbolic/abstract data, spatial/graphical data, and ideas were designed to be parallel to the complexity levels of dealing with data as indicated in the DOT (i.e., synthesizing, coordinating, analyzing, compiling, computing, copying, and comparing). If it was not possible to achieve a one-to-one correspondence by preserving the 7-point scale of complexity, levels of complexity thought to be reflective of the domain were identified in light of the other item development guidelines (e.g., “generating” as the most complex level of ideas and data).

4.2.1.2 Identifying Skills, Abilities, and Work Activities of Different Complexity Levels

To serve as a guide in item development, a second step was taken in identifying how abilities, skills, and work activities differ between occupations that span across the complexity levels. I refered to the O*NET database for the identification of required abilities, skills, and work activities. Once the DOT occupational complexity ratings were identified, example occupations of higher-complexity (with complexity ratings ranging from 70 to 80), moderate-complexity (with complexity ratings ranging from 55 to 69) and lower-complexity (with complexity ratings below 55) were found in the O*NET database and examined to see how these higher, moderate, and lower complexity occupational groups differed in terms of their characterizing features based on abilities, skills, and work activities. In identifying the cut-off points to classify the complexity levels as low, moderate, or high, I focused on the common characteristics of occupations and their data complexity level based on the DOT.

This analysis revealed (see Appendix D) that the higher-complexity groups were marked by work activities related to “thinking creatively;” abilities related to “originality,” “fluency of ideas,” and “inductive reasoning;” and skills related to “technology design,” “systems analysis,” and “operations analysis.” These characteristics were only observed among the higher-complexity occupations and not among the moderate or lower-complexity occupations. In light of these work characteristics, in addition to the “synthesizing” complexity levels of the DOT, another level of complexity, “generating,” was added. Items that would tap cognitively complex behavior were generated for this level. For example, “thinking creatively” and “originality” implied involvement with several of the data domains; therefore an item developed for the symbolic/abstract domain was “While thinking about a real world technical problem I would be interested in modeling it with mathematical statements (e.g. formulas)” (see Appendix E for examples of STEM Interest Complexity scale items, for each level of complexity).

The same analysis indicated that the moderate-complexity occupations were marked by work activities related to “processing information,” “updating and using relevant knowledge,” and “analyzing data or information;” abilities related to “mathematical reasoning,” “information ordering,” “visualization,” “oral expression,” “written and reading comprehension;” and skills related to “mathematics,” “science,” “complex problem solving,” and “critical thinking.” These characteristics were observed among the higher- and moderate-complexity occupations but not among the lower-complexity occupations. These characteristics corresponded to the DOT levels of analyzing, compiling, and computing (more advanced computations). I generated items that would tap cognitively complex behavior at these levels. For example, an item that would tap analyzing numerical data was developed based on the work activities of analyzing data or information: “When reading something technical, I like to analyze the numerical evidence they present to check its accuracy.”

The lower-complexity occupations did not possess the above-mentioned work activities, abilities, or skills, but were marked by work activities related to "operating vehicles, mechanized devices, or equipment" "inspecting equipment, structures, or material," "identifying objects, actions, and events," "getting information," and "estimating the quantifiable characteristics of products, events, or information;" abilities related to "gross body coordination," "manual dexterity," "control precision," "depth perception," "problem sensitivity," and "deductive reasoning;" and skills related to "equipment maintenance," "operation and control and monitoring," "installation," and "troubleshooting." These characteristics correspond to the DOT levels of compiling, simple computations, copying, and comparing. I generated items that would tap behavior at these levels. For example, the skills related to operations monitoring corresponded to a level of numerical comparing; thus, the following item was developed: "I would not mind keeping track of displays with numbers (like gauges)." Similarly, the skills related to installation corresponded to a level of spatial copying; thus, the following item was developed: "I can get frustrated while trying to assemble a 3-D object/system following instructions from the manual."

I formed items at different levels of complexity for each data involvement and idea domains, by analyzing the work activities, abilities, and skills of occupations at different complexity levels.

4.2.1.3 STEM Interest Complexity Assessed from a General Level

The General STEM Interest Complexity scale does not tap the underlying domains related to STEM areas—such as numerical, symbolic, or spatial—but was developed from a broader perspective in order to assess how much a person is interested in getting involved in increasingly advanced levels of STEM areas. The content of items also reflects the work activities and skills identified for low, moderate, and high-complexity jobs. In order of increasing complexity, the items correspond to: (1) getting the general idea, without going into technical jargon or detail (which is like a *hobby* level of interest); (2) acquiring more detailed and specialized knowledge, but without learning about the empirical studies that form the basis for the knowledge; (3) following the empirical literature in detail; (4) critically evaluating the empirical literature; and (5) formulating ideas to investigate. Examples that correspond to these levels from the areas of mechanics and machines and the human body are provided in Appendix F.

CHAPTER V

STUDY 1 HYPOTHESES AND METHOD

A survey of the personality correlates of the STEM groups that was presented under the section of "Characteristics of Engineers and Scientists" and the literature on personality-interest and personality-ability relationships revealed the following characteristics as potential correlates of the science/math trait complex: a tendency to be analytical, objective, and for rational decision-making (i.e., qualities of an MBTI Thinking type) as opposed to a decision making style based on feelings; being intellectually efficient and open to ideas; engaging in reasoning; being intellectually efficient; displaying psychological-mindedness (i.e., being insightful and competent); being achievement oriented; being rule-conscious; and showing characteristics of masculinity, self-control, self-sufficiency, low harm-avoidance, low sensitivity, low warmth, and low openness to feelings. Such personality dimensions, which are suggested as correlates of the STEM vocational tracks, were expected to converge with the science/math trait complex, while diverging from the other trait complexes.

The aforementioned personality characteristics are related to three major domains also identified by the narrative review in the preceding sections. The characteristics of intellectual efficiency, an inclination towards thinking rather than feeling, reasoning, and being open to ideas all appeared to be related to cognitively-oriented behavior. Rule-consciousness, masculinity, self-control, self-sufficiency, low harm-avoidance, low sensitivity, low warmth, and low openness to feelings all appeared to be related to toughmindedness. Finally, the MPQ achievement factor and the CPI achievement-via-conformance factors are achievement-oriented traits. The present study builds on the initial variables, which were identified as correlates based on effect size calculations by adding conceptually-related variables to the investigation. The scales used in this study are from the International Personality Item Pool Collaboratory (IPIP; Goldberg, 1999; Goldberg et al., 2006), which was developed to correspond to the personality constructs in the literature (e.g. FFM, 45 Abridged Big Five-Dimensional Circumplex facets, 16PF) and which was validated against existing personality measures, such as the NEO Personality Inventory, CPI, 16PF, and MPQ. The variables from the IPIP used in the present study are presented in Table 5.1, together with the corresponding measures which they were validated against. Definitions of these variables, together with their scale reliabilities and validities, are presented in Appendix G.

Table 5.1 Personality Scales from the IPIP

	IPIP Scale	Number of Items	Corresponding Measure
Cognitively-oriented behavior	Intellect -1	8	NEO-Personality Inventory, Openness to Ideas
	Intellect -2	9	16 PF Reasoning-Factor B
	Creativity-1	4	AB5C V+/II- vs V-/II+ facet
	Creativity-2	2	Hogan's Personality Inventory Intellectance
	Judgment	7	Values in Action (Peterson & Seligman, 2004)
	Planfulness-1	5	MPQ Control
Toughmindedness	Dutifulness	5	16PF Rule-Consciousness
	Forcefulness	9	CPI Masculinity
	Self-sufficiency	9	6-Factor Personality Questionnaire: Self-reliance
	Toughness	10	AB5C IV+/V+ vs IV-/V- facet
	Poise	6	CPI Toughmindedness
	Risk-avoidance	8	MPQ Harm-avoidance
	Warmth	7	16PF Factor A: Warmth
	Emotionality	7	NEO-PI O3: Openness to Feelings
Achieve-ment	Achievement-1	6	NEO-PI-R C4: Achievement striving
	Achievement-2	4	MPQ Achievement
	Achievement-3	3	6-Factor Personality: Achievement
	Planfulness-2	6	CPI Achievement-via-Conformance

Notes. 16PF B: 16 Personality Factor Questionnaire; AB5C V+ II-: Abridged Big Five-Dimensional Circumplex agreeableness factor; MPQ: Multidimensional Personality Questionnaire; CPI: California Personality Inventory.

5.1 Study 1 Hypotheses

Cognitively-oriented behavior, toughmindedness, and achievement were hypothesized to be associated with individuals who chose to enter STEM-related majors in college. In order to carry out this investigation, these personality variables are subjected to a series of analyses with an undergraduate college student sample from the schools of engineering, sciences, social sciences, humanities, arts, and business.

5.1.1 Exploration of the Factor Structure

I suggest that these personality variables will underly three factors; cognitively-oriented behavior, toughmindedness, and achievement orientation.

Hypothesis 1. A three-factor model is expected to fit the data.

I hypothesize that the scales related to creativity, intellect, judgment, and planfulness will be indicators of cognitively-oriented behavior. Dutifulness, poise, forcefulness, self-sufficiency, low toughness, risk-avoidance, low warmth, and low emotionality will be indicators of toughmindedness. The achievement striving and planfulness scales will be indicative of the achievement factor. The hypothesized model's fit to the data is tested via Confirmatory Factor Analysis (CFA).

Hypothesis 2. Cognitively-oriented behavior, toughmindedness, and achievement are expected to show discriminant relations with the broad Big Five factors. However, due to partial conceptual overlap, cognitively-oriented behavior is expected to have a small association with openness to experience (based on the intellect scale that corresponds to the openness to ideas facet), and achievement is expected to have a moderate association with conscientiousness (as achievement is one of the conscientiousness facets), even though item promiscuity was avoided.

5.1.2 Differentiation of School Membership

I suggest that cognitively-oriented behavior, toughmindedness, and achievement will differentiate students who are in the STEM-related majors from students who are in non-STEM-related majors such as the humanities, social sciences, business, or arts schools. As the literature review revealed that engineering and scientist groups were similar to each other in terms of the requirements and work activities of their fields in the modern day (ABET, 1990; Duffy, 1996; Kenyon, 1993; Reynolds, 1991), these two groups were combined and treated as one group.

The literature review revealed that STEM groups were different from non-STEM groups on some personality constructs. Effect sizes based on Hedges' $\hat{g}$ for differences between these groups ranged from .30 to 2.35 (see Table 2.1 and Appendices A and B). I expect to find a medium size of difference (Hedges' $\hat{g}$ = .50) between students in STEM-related and non-STEM related majors based on the hypothesized personality variables.

Hypothesis 3a. Students enrolled in STEM majors will score higher on the hypothesized personality variables at the scale level than students enrolled in non-STEM majors. This hypothesis is evaluated by computing independent samples *t*-test analyses and effect sizes of the group differences based on Hedges' $\hat{g}$.

Personality, in addition to interests, can play a role in choosing the realistic and investigative environments. A discriminant function characterized by realistic interests, introversion, and thinking was related to vocational choice in terms of discriminating the realistic and investigative theme-related academic majors from other vocational theme-related majors (Pulver, 2004). Personality scales alone resulted in 35% correct classification of students into academic majors.

Hypothesis 3b. Students enrolled in STEM majors will be discriminated from those enrolled in non-STEM majors. This hypothesis will be tested using Discriminant Function Analysis based on composites of the three personality factors for the prediction of school membership of students. I expect that cognitively-oriented behavior, toughmindedness, and achievement will discriminate between groups with a correct classification percentage of at least 30% as suggested in the literature.

5.1.3 Convergence with the Science/Math Trait Complex

Cognitively-oriented behavior, toughmindedness, and achievement are expected to converge with the science/math trait complex. To test this, these personality factors are correlated with the vocational interests, cognitive abilities, and self-concepts characterizing the science/math trait complex.

5.1.3.1 Vocational Interests

Personality scales of the present study have been reported to have small to moderate associations with realistic and investigative interests (r range = .20 to .50).

Hypothesis 4. Cognitively-oriented behavior, toughmindedness, and achievement will show converging associations with realistic and investigative interests, with correlations ranging from .20 to .50, and will show discriminating associations with the other interest themes, as indicated by negligible correlations (lower than .20).

5.1.3.2 Self-concept

Science, math, and spatial self-concepts have been reported to be associated with the science/math trait complex (Ackerman et al., 2001).

Hypothesis 5. Cognitively-oriented behavior, toughmindedness, and achievement will have significant moderate correlations with the science, math, and spatial self-concepts (ranging from .20 to .40), whereas these personality factors are expected to have lower positive correlations with the verbal self-concept.

5.1.3.3 Cognitive Abilities

Math (r = .30) and spatial abilities (r = .40) are the cognitive ability markers of the science/math trait complex (Ackerman, 2000; Ackerman et al., 2001; Ackerman & Heggestad, 1997; Ackerman & Rolfhus, 1999). The literature on personality and cognitive ability relations shows moderate associations (r range = .24 to .45).

Hypothesis 6. Cognitively-oriented behavior, toughmindedness, and achievement will show significant moderate correlations (between .30 and .45) with math and spatial abilities. The personality variables are expected to show lower but still significant correlations with verbal abilities, due to positive manifold between ability measures.

5.1.3.4 Factor Structure

Exploring the factor structure of personality (i.e., cognitively-oriented behavior, toughmindedness, achievement, and the Big Five factors), interest, and ability domains would further suggest how these personality variables are interrelated with ability and interest variables. I expect that cognitively-oriented behavior, toughmindedness, and achievement will load together with the science/math complex markers of realistic and investigative interests, science, math, and spatial self-concepts, and not together with the other ability, self-concept, and interest variables characteristic of other trait complexes.

5.2 Initial Assessment of the STEM Interest Complexity Scales

The purposes of including the STEM Interest Complexity scales (i.e., numerical data, symbolic/abstract data, spatial/graphical data, ideas, and the General STEM Interest Complexity scale) in Study 1 were to: 1) pilot test the new measure in terms of the factor structure based on the proposed content domains, test the scale reliabilities, and test the associations with vocational criteria; and 2) drop items/scales or make refinements before investigating the new measure's validity in Study 2.

5.3 Study 1 Method

5.3.1 Sample and Procedure

For each of the statistical analyses the required sample sizes were computed for a power of at least .80. For CFA, a sample size of 100 gives a power over .80 with 50 degrees of freedom and gives a power of .96 with 20 degrees of freedom (Loehlin, 2004). For the hypothesized three-factor personality model with 18 personality variables and 150 degrees of freedom, a sample of 100 individuals provides adequate power to reject the hypothesis of poor fit (RMSEA > .10). A power analysis indicated that to find a moderate size of difference (Cohen's d = .5) a sample size of 140 provides a power of .90. A power analysis for bivariate correlations indicated that a sample size of 150 provides a power of .80 to find an effect size as small as r = .20 (Cohen, 1988). For exploratory factor analysis, a sample of 150 has been suggested as sufficient for solutions with high loadings (Guadagnoli & Velicer, 1988). Accordingly, a sample of at least 150 individuals was necessary for Study 1.

A total of 289 participants signed up for the study and started the online survey part of Study 1. Of these, 279 completed the survey entirely (96.5% response rate) and 10 completed partially, responding to between 25% and 75% of the survey. Of the participants who completed the survey, 189 also participated in the in-class cognitive ability testing session (67.7% response rate). Of those who participated in the in-class testing, 170 granted permission to access their transcripts (89.9% response rate). Survey data were checked for random responding. If a participant took less than half the required time to complete the survey, as indicated by the report provided by SurveyMonkey, the case was deleted, since a pilot test indicated that it took at least 45-50 minutes to go through the entire survey as long as the responder read all the items. Some cases were identified to have responded using the same scale value across an entire scale(s) for all non-reverse and also reverse scored items. Such cases were also deleted. As a result, five cases were deleted, and 274 survey responses, 184 cognitive ability test responses, and 166 transcripts were retained for analyses.

Participants' age ranged from 18 to 25, and the gender ratio was 46% men and 54% women. The sample consisted of 30.3% freshmen, 30.3% juniors, 19% sophomores, 13.1% seniors, and 6.2% who were in the 5th year of their undergraduate education. In terms of college major breakdown, 184 (67%) participants were in a STEM major. Of these, 130 completed the cognitive ability tests and 120 provided transcripts. Ninety (33%) were in a non-STEM major. Of this group, 54 completed cognitive ability tests and 46 provided transcripts. Among STEM majors, 106 (38.7%) participants were enrolled in an engineering major, 41 (15%) were enrolled in computer sciences, 32 (11.7%) were enrolled in biological sciences, and five (1.8%) were enrolled in mathematics.

Students were recruited from those who enroll in the General Psychology courses. The students who volunteered to participate in exchange for extra course credit were administered the questionnaire package in two parts. The non-ability tests (Part 1) were uploaded on the Internet and students responded to the survey online. Completion of Part 1 took approximately one hour. The ability tests (Part 2) were administered in paper and pencil format in a classroom setting. Participants were assigned to study sessions according to their availability. One study session for Part 2 lasted for 90 minutes.

5.3.2 Measures

The measures administered in Study 1 were the 18 scales from the IPIP, the Big Five personality scales from the IPIP, the Unisex Edition of the American College Testing Interest Inventory (UNIACT), self-concept scales, cognitive ability measures, the newly developed STEM Interest Complexity scales, a newly developed scale to assess intentions to persist in and further pursue STEM-related vocational tracks (see Appendix H), and demographic questions. Each measure is described below with their psychometric properties reported in the literature.

5.3.2.1 Personality Scales

The personalities of STEM majors were investigated with 18 scales from the IPIP (Goldberg, 1999; Goldberg et al., 2006): two intellect scales, two creativity scales, judgment, planfulness (MPQ-control), dutifulness, forcefulness, self-sufficiency, poise, toughness, risk-avoidance, warmth, emotionality, three achievement striving scales, and planfulness (CPI achievement-via-conformance). Items that had the same or very similar counterparts in other scales (including the Big Five factor scales), items that were not face valid, and items that were ambiguous were dropped. A total of 115 items were included (see Table 5.1 for the number of items in each IPIP scale). The Big Five factors were assessed with the related IPIP scales, with 10 items in each scale. Items were rated on a 6-point Likert-type scale, ranging from “very untrue of me” to “very true of me.”

The IPIP scales included in the study were reported to have internal consistency reliabilities ranging from .71 to .86 (except for the self-sufficiency scale, which was .59). The IPIP scales were developed to model the personality constructs assessed by various personality instruments such as the NEO-PI-R, 16PF, MPQ, and CPI, and were validated based on their associations with the related scales from these instruments (Goldberg et al., 2006). Appendix G provides descriptions of each of the IPIP scales included in the present study, together with their reliabilities and validity coefficients.

5.3.2.2 Vocational Interests

Vocational interests were assessed with the UNIACT (Lamb & Prediger, 1981), which measures Holland’s (1959, 1997) RIASEC interests. Ackerman et al. (2001) reported internal consistency reliabilities ranging from .83 to .92. Construct validity coefficients with the Strong-Campbell Inventory-II ranged from .74 to .90 (Lamb & Prediger, 1981). Each interest theme was assessed with 15 items, with a total of 90 items. Each item was rated on a 6-point scale ranging from “strongly dislike” to “strongly like.”

5.3.2.3 Self-concept Measures

Self-concepts of competencies were assessed using a 30-item measure developed by Ackerman and colleagues (Ackerman & Goff, 1994; Ackerman, Kanfer, & Goff, 1995; Ackerman et al., 2001; Ackerman & Rolfhus, 1999; Kanfer et al., 1996) that covered the verbal, math, spatial, and science domains, with internal consistency reliabilities of.84, .87, .84 and .91, respectively. Validity of the scales was shown based on the correlations with Ackerman's (2000) trait complexes. The instructions directed the participants to "consider whether you have the skill or ability, keeping in mind that most people vary in the kinds of skills and abilities that they have." A sample item is "I understand the basis of many mathematical concepts." Items were rated on a 6-point Likert-type scale ranging from "strongly disagree" to "strongly agree."

5.3.2.4 Intentions to Persist in and Further Pursue a STEM Field

A new scale developed to assess intentions to persist in STEM-related areas was included in Study 1 to carry out initial item- and scale-level analysis (see Chapter 8 for more information on the development of this scale). The scale included 12 items that assessed intentions to stay in the current major, STEM degree attainment intentions, and long-term career intentions in STEM-related areas (see Appendix H). Items were rated on a 6-point Likert-type scale ranging from "very untrue of me" to "very true of me." Internal consistency reliabilities of the scale factors ranged between .79 and .88.

5.3.2.5 Demographic Information

Participants were asked to provide their sex, college major, year in major, and SAT scores, as well as some experiential questions about the math/science classes they took in high school, and whether they participated in STEM competitions or clubs in high school or in college. In addition, participants were asked to provide the experimenters with permission to obtain their transcripts for course enrollment and grade information.

5.3.2.6 Cognitive Ability Measures

Math/numerical reasoning, verbal, and spatial abilities were assessed with tests from the ETS Kit (Ekstrom, French, Harman, & Dermen, 1976). Math/numerical reasoning abilities were assessed with the Arithmetic Aptitude Test, Mathematic Aptitude Test, and the Necessary Arithmetic Operations Test. Verbal abilities were assessed with the Controlled Associations Test, Making Sentences Test, and the Extended Range Vocabulary Test. Spatial abilities were assessed with the Cube Comparison Test, Paper Folding Test, and Surface Development Test. The math/numerical, verbal, and spatial ability tests took 25, 26, and 15 minutes respectively, lasting for a total of 90 minutes, including time spent on administration procedures. Descriptions of the tests are provided in Appendix G. The ETS Kit Manual reported that the alternate form reliabilities of the tests ranged from .73 to .91.

5.3.2.7 STEM Interest Complexity Scales

The development of the STEM Interest Complexity scales is presented in the previous section. The purpose of including these scales in Study 1 was to pilot test the new measure’s psychometric properties and associations with vocational criteria, and to refine the items if necessary. The total number of items included was 127. There were 28 items (8 reverse coded) assessing interest complexity for dealing with numerical data, 30 items (9 reverse coded) for dealing with symbolic data, 24 items (7 reverse coded) for dealing with spatial data, 30 items (10 reverse coded) for dealing with ideas, and 15 items assessing general level of complexity in STEM-related areas. Items were rated on a 6-point Likert-type scale, ranging from “very untrue of me” to “very true of me.” Internal consistency reliabilities ranged from .72 to .95.

CHAPTER VI

STUDY 1 RESULTS: PERSONALITY CORRELATES AND PRELIMINARY FINDINGS ON THE NEW INTEREST MEASURE

The first part of Chapter 6 is devoted to the presentation of findings pertaining to the investigation of personality variables in relation to the science/math trait complex. The second part of Chapter 6 is devoted to the presentation of initial results obtained from the newly developed STEM Interest Complexity scales.

6.1 Investigating the Personality Correlates of the Science/Math Trait Complex

In this section, the factor structure of constructs is presented first, followed by descriptive statistics of the study variables. Then, results of hypotheses testing are presented. Finally, results from an exploration of the trait complex/STEM vocational criteria associations are presented.

6.1.1 Preliminary Tests for Factor Structures

Preliminary tests were conducted to investigate the factor structure of personality and cognitive abilities. Based on these factor structures, factor composites were formed by adding the unit-weighted z-scores of the factor indicators. Further analyses were conducted using these factor composites. Descriptive statistics are provided for the personality scales and the cognitive ability tests in Table 6.1.

Table 6.1 Descriptives for Personality Scales and Cognitive Ability Tests

	# of items	Mean	Sd	Range	Skewness	α
Personality Scales						
Intellect-1	8	4.23	0.73	3.75	-0.22	.80
Intellect-2	9	4.36	0.59	3.22	0.09	.74
Creativity-1	4	4.27	0.71	4.25	-0.24	.62
Creativity-2	2	4.60	0.89	5.00	-0.63	.45
Judgment	7	4.55	0.61	3.57	-0.25	.76
Planfulness-1	6	3.81	0.76	4.17	-0.03	.72
Dutifulness	5	4.00	0.92	4.80	-0.76	.85
Forcefulness	9	3.98	0.71	4.22	-0.18	.81
Self-sufficiency	9	3.79	0.60	3.78	0.09	.64
Toughness	10	4.06	0.71	4.30	-0.06	.83
Poise	6	3.92	0.68	4.50	-0.28	.63
Risk-avoidance	8	3.42	0.93	5.00	0.10	.88
Warmth (reversed)	7	2.60	0.65	3.57	0.23	.74
Emotionality (reversed)	7	2.67	0.77	4.00	0.20	.79
Achievement-1	6	4.47	0.75	4.33	-0.55	.83
Achievement-2	4	4.74	0.72	4.00	-0.61	.70
Achievement-3	3	4.04	0.98	4.67	-0.20	.73
Planfulness-2	5	4.42	0.72	4.20	-0.63	.74
Ability Tests						
Arithmetic Aptitude	15	8.81	2.58	15	-0.27	
Mathematic Aptitude	15	6.20	2.71	12.75	0.15	
Arithmetic Operations	15	8.78	2.62	14.25	0.01	
Controlled Associations	8*8	26.40	8.14	38	0.35	
Making Sentences	20	17.55	2.54	12	-1.26	
Extended Vocabulary	48	20.90	6.32	31	0.26	
Cube Comparisons	24	11.56	4.21	21	0.26	
Paper Folding	10	7.28	2.00	8	-0.56	
Surface Development	6*5	20.65	7.96	30	-0.69	

Notes. Internal consistency reliabilities of the ability tests could not be computed as data on individual items were not recorded. Standard error of skewness for personality scales is .15 and for ability tests is .18.

Personality scales had acceptable levels of internal consistency reliabilities, with the exception of the creativity-2 scale, which had two items. Four of the 18 personality scales (creativity-2, dutifulness, achievement-1, achievement-2, and planfulness-2) and three of the nine cognitive ability tests (making sentences, paper folding, surface development) were negatively skewed. Scales were converted to z-scores to obtain factor score composites to be used in further analyses.

6.1.1.1 Personality Factor Structure

Following Hypothesis 1, the 18 personality scales from the IPIP were subjected to a CFA, where three personality factors were specified: cognitively-oriented behavior, toughmindednes, and achievement. All indicators were freely estimated and the factor variances were set to equal one. The three factors were allowed to correlate. The hypothesized 3-factor model did not fit the data ($\chi^2(132) = 1191.130$, $p < .01$ $CFI = .63$, $RMSEA = .17$). Four indicators had loadings less than .40, so a nested model was tested by dropping these indicators. Planfulnes was dropped from cognitively-oriented behavior, and dutifulness, risk-avoidance, and warmth were dropped from toughmindedness. Even though the reduced model had improved fit indices, it still did not show adequate fit to the data ($\chi^2(74) = 425.407$, $p < .01$ $CFI = .84$, $RMSEA = .13$). Thus, Hypothesis 1 was rejected. The factor loadings for both of the models can be seen in Table 6.2.

Upon observing that the hypothesized 3-factor model did not fit the data well, I decided to explore the number of factors using Exploratory Factor Analysis (EFA). Following the guidelines of Horn (1965) and Montanelli and Humphreys (1976), a parallel analysis was performed in which random data-generated eigenvalues were compared against real data eigenvalues. All eigenvalues were estimated based on principal axis factoring, in which the correlation matrix to be analyzed had squared multiple correlations on the diagonal. Since widely-used statistical programs do not provide eigenvalues based on principal axis factoring by default, syntax codes developed by O’Conner (2000) were used to obtain parallel analysis results in SPSS. The scale of warmth was not included in further analyses due to its low shared variance.

Table 6.2 CFA Loadings of the Personality Factors based on two Models

	Model 1	Model 2
Factor I: Cognitively-oriented behavior		
Intellect-1	.776	.777
Intellect-2	.951	.951
Creativity-1	.770	.772
Creativity-2	.480	.481
Judgment	.520	.515
Planfulness-1	.140	-
Factor II: Toughmindedness		
Dutifulness	-.198	-
Forcefulness	.768	.767
Self-sufficiency	.683	.666
Toughness	.900	.900
Poise	.772	.786
Risk-taking	.283	-
Low Warmth	-.015	-
Low Emotionality	.398	.399
Factor III: Achievement		
Achievement-1	.904	.904
Achievement-2	.857	.857
Achievement-3	.675	.676
Planfulness-2	.689	.689

Note. All loadings, except for that of Warmth, are significant at the .05 level.

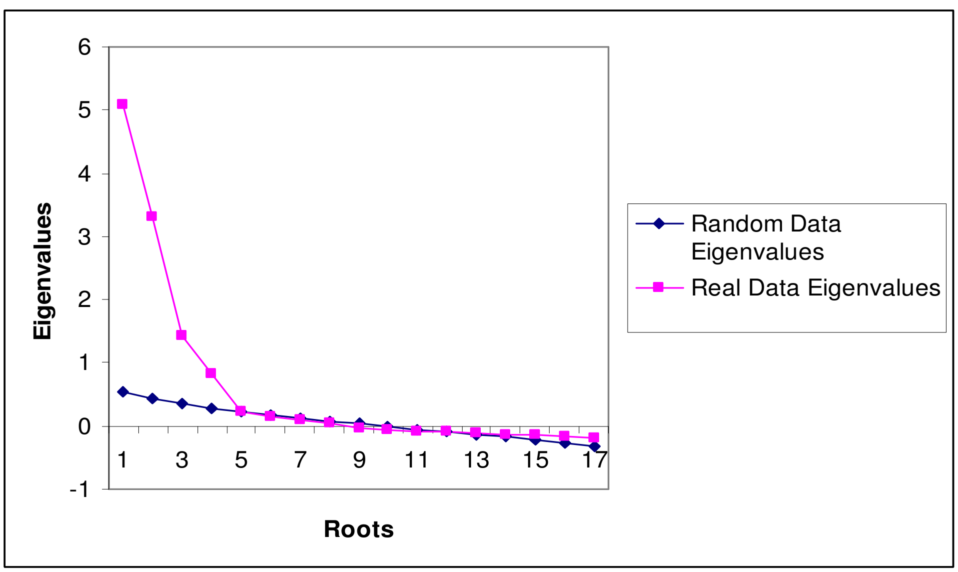

Figure 6.1 Parallel Analysis for Determining the Number of Personality Factors

Parallel analysis results revealed that real data eigenvalues exceeded their random data eigenvalue counterparts in four roots (see Figure 6.1). The scales were subjected to Principal Axis Factoring (PAF) with Oblique rotation (direct oblimin) by extracting a 4-factor solution. The unrotated 4-factor solution explained 64% of variance. Examination of the pattern and structure matrices indicated that the scales of planfulness-1 and judgment (originally hypothesized as cognitively-oriented behavior indicators) and dutifulness and risk-avoidance (originally hypothesized as toughmindedness indicators) were actually forming a separate factor. These four factors were hypothesized to form a fourth factor of "control." The remaining scales loaded on the three factors of cognitively -oriented behavior, toughmindedness, and achievement, as was expected. Scale intercorrelations are presented in Table 6.3 and pattern maxtrix loadings in Table 6.4.

Each of the identified four-factors were subjected to a series of CFAs to determine the best fitting model of indicators. Results are summarized in Table 6.5. Four nested models were tested for toughmindedness. The originally hypothesized model, which also included two of the control factor variables, indeed suggested poor fit to the data ($\chi^2(20) = 324.63$, $p < .01$ $CFI = .65$, $RMSEA = .24$). The following nested models were formed by dropping the indicator with the lowest loading. Based on chi-square difference tests, Model 3 appeared to be the best fitting model of indicators for toughmindedness ($\chi^2(2) = 13.12$, $p < .01$ $CFI = .97$, $RMSEA = .14$), with toughness, self-sufficiency, poise, and low-emotionality as indicators. The originally hypothesized model for cognitively-oriented behavior was compared to two nested models. Chi-square difference tests indicated that the best fitting model of indicators was the one with the intellectance and creativity scales ($\chi^2(2) = .401$, $p > .05$ $CFI = 1.00$, $RMSEA = 0.00$).

Table 6.3 Personality Scale Intercorrelations

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1.Intellect-1	1.00															
2.Intellect-2	.74**	1.00														
3.Creativity	.64**	.73**	1.00													
4.Creativity-2	.41**	.45**	.41**	1.00												
5.Judgment	.30**	.51**	.34**	.21**	1.00											
6.Planfulness-1	.04	.13*	-.04	-.06	.54**	1.00										
7.Dutifulness	-.20**	-.21**	-.32**	-.24**	.32**	.60**	1.00									
8.Forcefulness	.24**	.42**	.43**	.24**	.28**	-.01	-.10	1.00								
9.Self-sufficient	.28**	.37**	.37**	.19**	-.01	-.28**	-.41**	.44**	1.00							
10.Toughness	.39**	.48**	.41	.18**	.24**	-.05	-.16**	.68**	.63**	1.00						
11.Poise	.29**	.47**	.33**	.14**	.34**	.21**	.02	.67**	.49**	.69**	1.00					
12.Risk-avoidant	.01	-.04	-.22**	-.13*	.29**	.57**	.48**	-.33**	-.35**	-.23**	-.09	1.00				
13.Emotionality	.07	.01	.06	.15*	.02	.06	.06	-.20**	-.43**	-.42**	-.27**	-.03	1.00			
14.Achievement-1	.28**	.41**	.34**	.23**	.54**	.46**	.35**	.41**	.01	.18**	.37**	-.11	-.08	1.00		
15.Achievement-2	.22**	.36**	.26**	.18**	.54**	.54**	.38**	.32**	-.01	.11	.35**	-.16**	-.06	.77**	1.00	
16.Achievement-3	.18**	.25**	.21**	.16**	.29**	.31**	.22**	.39**	.05	.16**	.31**	.02	-.05	.61**	.60**	1.00
17.Planfulness-2	.11	.25**	.09	.18**	.57**	.61**	.45**	.31**	-.03	.18**	.42**	-.28**	.00	.63**	.60**	.44**

Notes. $N = 274$. * $p < .05$; ** $p < .01$.

Table 6.4 EFA of the Four-factor Personality Structure

	I	II	III	IV	h^2
Factor I: Cognitively-oriented behavior					
Intellect-1	**.895**	-.164	.146	.015	.763
Intellect-2	**.827**	-.128	.030	-.093	.629
Creativity-1	**.765**	.127	.043	.085	.637
Creativity-2	**.503**	.132	-.106	.120	.325
Factor II: Control					
Risk-avoidance	-.033	**-.795**	.090	.158	.493
Planfulness-1	-.015	**-.713**	-.002	.331	.661
Dutifulness	-.373	**-.520**	-.053	.374	.590
Judgment	.351	**-.468**	.091	.309	.581
Factor III: Toughmindedness					
Toughness	.235	.028	**.808**	.037	.722
Poise	.126	-.061	**.656**	.314	.655
Self-sufficiency	.222	.251	**.624**	-.085	.581
Low Emotionality	-.191	-.062	**.620**	-.134	.360
Forcefulness	.089	.295	**.514**	**.494**	.675
Factor IV: Achievement					
Achievement Striving-1	.138	-.076	-.053	**.811**	.704
Achievement Striving-2	.093	-.153	-.057	**.766**	.861
Achievement Striving-3	-.011	.110	-.012	**.729**	.459
Planfulness-2	-.086	-.362	.137	**.591**	.622

Notes. N = 274. Factor loadings above .40 are shown in bold type.

For the achievement factor, the model with the originally hypothesized scales of achievement-1, achievement-2, achievement-3, and planfulness-2 fit the data well ($\chi^2(2) = 1.86$, $p > .05$ $CFI = 1.00$, $RMSEA = 0.00$). Finally, a model including planfulness-1, risk-avoidance, dutifulness, and judgment as indicators of the control factor was tested and indicated good fit to the data ($\chi^2(2) = 9.10$, $p > 0.01$, $CFI = .98$, $RMSEA = .11$). The four factors together were also subjected to a CFA by specifying the cross-loading variables with loadings higher than .40 as factor indicators ($\chi^2(91) = 456.13$, $p < 0.01$, $CFI = .86$, $RMSEA = .12$). A chi-square difference test indicated that the 4-factor model was better fitting than the initial 3-factor model ($\chi^2(41) = 735$, $p < 0.001$).

Table 6.5 CFA Summary for Personality Factor Indicators

	χ^2 (df)	*CFI*	*RMSEA*	NOTES	χ^2 difference
Toughmindedness Indicators					
Model 1: Dutiful, Forceful, Self-suff, Toughness, Poise, Risk-avoid, Warmth, Emotion	324.6 (20)	.65	.24	Warmth and Dutiful have zero loadings, risk-take has a small loading.	-
Model 2: Forceful, Self-suff, Toughness, Poise, Emotion	44.3 (5)	.93	.17		$\chi^2(15)=280.4$ $p < .001$
**Model 3*: Self-suff, Toughness, Poise, Emotion	13.1 (2)	.97	.14		$\chi^2(3) = 31.1$ $p < .001$
Model 4: Self-suff, Toughness, Poise	16.9 (2)	.97	.17		-
Cognitively-Oriented Behavior Indicators					
Model 1: Intel1, Intel2, Creat1, Creat2, Judge, Plan1	138. 2 (9)	.82	.23	Planfulness has small loading.	-
Model 2: Intel1, Intel2, Creat1, Creat2, Judge	19.9 (5)	.96	.10		$\chi^2(4) = 118.3$ $p < .001$
**Model 3*: Intel1, Intel2, Creat1, Creat2	0.4 (2)	1.00	.00		$\chi^2(3) = 19.5$ $p < .001$
Achievement Indicators					
**Model 2*: Ach1, Ach2, Ach3, Plan2	1.7 (2)	1.00	.00		
Control Indicators					
**Model 1*: Judge, Plan1, Dutiful, Risk-avoid	9.1 (2)	.98	.11		
4-Factor Model: Toughmindedness: Self-suff, Toughness, Poise, Emotion (low) Cognitively-oriented behavior: Intel1, Intel2, Creat1, Creat2 Achievement: Ach1, Ach2, Ach3, Plan2 Control: Judge, Plan1, Dutiful, Risk-avoid	456.1 (41)	.86	.12		

Notes. $N = 274$. (*) indicates best fitting model. Dutiful (Dutifulness, 16PF:Rule-consciousness), Forceful (Forcefulness, CPI:Masculinity), Self-suff (Self-sufficiency, 6FPQ:Self-reliance), Toughness (Toughness, AB5CIV+V+), Poise (Poise, CPI:Tough-mindedness), Risk-avoid (Risk-avoidance, MPQ:Harm-avoidance), Warmth (16PF:Warmth), Emotion (Emotionality, NEO:O3), Intel1 (Intellectance1, NEO:O5), Intel2 (Intellectance 2, 16PF:B), Creat1 (Creativity1, AB5CV+II-), Creat2 (Creativity2, Hogan Intellectance), Judge (Judgment, VIA), Plan1 (Planfulness1, CPI: Masculinity), Ach1 (Achievement1, MPQ:Ach), Ach2 (Achievement2, NEO:C4), Ach3 (Achievement3, 6FPQ:Ach), Plan2 (Planfulness2, CPI:Achievement-via-conformance). CFI: Confirmatory Fit Index, RMSEA: Root Mean Square Error of Approximation.

Based on the best fitting model of indicators, factor composites were obtained using unit-weighted z-scores. Descriptive statistics, intercorrelations and internal consistency reliabilities of the personality factors are presented in Table 6.6.

Table 6.6 Descriptive Statistics for the Hypothesized Personality Factors

	M	Sd	Range	Skew	TM	COB	ACH	C
Toughmindedness (TM)	0	1	6.29	-0.14	(.78)			
Cognitive-orientation(COB)	0	1	6.44	-0.22	.55**	(.82)		
Achievement (ACH)	0	1	5.60	-0.52	.32**	.34**	(.85)	
Control (C)	0	1	5.75	-0.28	.05	.01	.58**	(.77)

Notes. Descriptives are based on standardized unit-weighted z-score composites. Standard error of skewness is .15. Numbers in parentheses are Cronbach's alpha internal consistency reliabilities. $N = 274$. * $p < .05$; ** $p < .01$.

6.1.1.2 Cognitive Ability Factor Structure

Nine tests from the ETS Kit of Factor Reference Tests were used to assess math, verbal, and spatial abilities. A CFA was performed to test for the 3-factor structure. Arithmetic aptitude, mathematic aptitude, and necessary arithmetic operations tests were specified as the math ability factor indicators; cube comparisons, paper folding, and surface development tests were specified as the spatial ability factor indicators; and controlled associations, making sentences, and extended range vocabulary tests were specified as the verbal ability factor indicators. The model fit the data well ($\chi^2(24) = 36.605$, $p = 0.05$, $CFI = .96$, $RMSEA = .05$). Factor loadings are presented in Table 6.7 and factor intercorrelations are presented in Table J.1.

Table 6.7 CFA Loadings of the Cognitive Ability Factors

	CFA Loading
Factor I: Math Abilities	
Mathematic Aptitude	.800
Arithmetic Aptitude	.740
Necessary Arithmetic Operations	.628
Factor II: Verbal Abilities	
Controlled Associations	.629
Extended Range Vocabulary	.558
Making Sentences	.491
Factor III: Spatial Abilities	
Cube Comparisons	.703
Surface Development	.696
Paper Folding	.686

$N = 185$.

6.1.2 Decriptive Statistics for the Related Constructs

Descriptive statistics for the variables, which were subjected to correlation analyses to test their hypothesized associations with the four personality factors, are presented in this section. These variables include cognitive abilities, RIASEC vocational interests assessed with the UNIACT, self-concept measures, and personality factors based on the Big Five model. Means, standard deviations, ranges, and skewness values are presented in Table 6.8. Variable intercorrelations are presented in Table J.2.

Tabel 6.8 Decriptive Statistics for Ability, Vocational Interest, Self-concept, and the Big Five Personality Variables

	N	Number of items	Mean	Sd	Range	Skewness	α
1. SAT Verbal	212		648.12	71.21	400.00	-0.39	-
2. SAT Math	220		680.73	71.23	350.00	-0.32	-
3. ETS Math	185		0	1.00	5.80	0.21	-
4. ETS Verbal	185		0	1.00	5.34	-0.16	-
5. ETS Spatial	185		0	1.00	4.61	-0.25	-
6. Realistic	274	15	3.56	0.88	4.67	-0.42	.90
7. Investigative	274	15	3.85	0.92	4.93	-0.32	.91
8. Artistic	274	15	3.85	1.00	4.73	-0.26	.91
9. Social	274	15	4.36	0.73	4.20	-0.52	.87
10. Enterprising	274	15	3.74	0.82	4.87	-0.40	.88
11. Conventional	274	15	3.23	1.03	4.87	0.04	.94
12. Math SC	274	5	4.52	1.05	5.00	-0.95	.91
13. Science SC	274	6	4.24	1.05	5.00	-0.74	.92
14. Spatial SC	274	13	4.59	0.83	4.62	-0.40	.91
15. Verbal SC	274	6	4.76	0.80	3.67	-0.53	.83
16. Big Five: O	274	10	4.29	0.78	4.10	-0.49	.80
17. Big Five: C	274	10	4.14	0.78	4.00	-0.36	.88
18. Big Five: N	274	10	2.87	0.83	4.80	0.74	.89
19. Big Five: E	274	10	3.98	0.85	4.60	-0.43	.79
20. Big Five: A	274	10	4.27	0.63	3.70	-0.55	.91

Notes. The ETS Kit ability composites have been restandardized. Internal consistency reliabilities of ability tests could not be computed as data on individual items were not recorded. Standard error of skewness is 0.17 for the SAT scores, is 0.18 for the ETS Kit ability composites, and is 0.15 for the non-ability variables. ETS: Educational Testing Service, SC: self-concet measure, O: Openness to Experience, C: Conscientiousness, N: Neuroticism, E: Extraversion, A: Agreeableness.

6.1.3 Personality and Science/Math Trait Complex Associations

Once the personality factor structure was identified, personality factor composites were formed by summing the unit-weighted z-scores of indicators based on the best fitting model. These four personality factors were used in hypotheses testing to reveal their associations with the science/math trait complex and the STEM student groups.

As indicated in Hypothesis 2, the proposed personality factors were expected to have discriminant relations with the broad Big Five factors, except for the associations between achievement and conscientiousness and between cognitively-oriented behavior and openness to experience. The hypothesized four personality factors had significant strong associations with the Big Five factors (see Table 6.9). As expected, notable correlations were observed between achievement and conscientiousness (r = .83) and between cognitively-oriented behavior and openness to experience (r = .55). In addition, notable correlations were observed between toughmindedness and neuroticism (r = -.64) and between control and conscientiousness (r = .58). Thus, Hypothesis 2 was not supported as the hypothesized personality factors did not have discriminant relations with the Big Five factors.

Table 6.9 Correlations between the Hypothesized Personality Factors and the Big Five Factors

	Openness	Conscientiousness	Extraversion	Agreeableness	Neuroticism
Toughmindedness	.05	.32**	.26**	.11	-.64**
Cognitive-orient	.55**	.24**	.26**	.00	-.23**
Achievement	.04	.83**	.28**	.33**	-.31**
Control	-.20**	.58**	-.14*	.24**	-.07

* $p < .05$; ** $p < .01$.

In Hypothesis 3a, I predicted that STEM major students would score significantly higher on the personality scales. Based on independent samples *t*-test analyses STEM majors were significantly different only on the emotionality scale, an indicator of toughmindedness, in which STEM majors scored lower ($M = 4.23$) than non-STEM majors ($M = 4.56$) with a moderate effect size ($t(272) = 3.36$, $p < .01$; Hedges' $\hat{g} = 0.44$). No other significant mean differences were observed between STEM and non-STEM majors (see Table 6.10). Thus, Hypothesis 3a was for the most part not supported. No significant mean differences were found on the factor level. The Big Five factors were also tested for group mean differences. Only openness to experience showed a significant group difference ($t(272) = 2.75$, $p < .01$; Hedges' $\hat{g} = 0.36$), with non-STEM majors scoring higher ($M = 4.47$) than STEM majors ($M = 4.19$) (see Table 6.10).

In Hypothesis 3b, I predicted that the hypothesized personality factors would discriminate students between STEM and non-STEM majors, with at least a 30% correct classification. However, as mentioned above, no group differences were observed for the hypothesized personality factors, but a group difference was observed for the emotionality scale. Therefore testing for Hypothesis 3b was revised to include only the toughmindedness indicators. A Discriminant Function Analyses (DFA) was performed to predict school membership based on the scales of toughness, poise, self-sufficiency, and emotionality. The DFA, which used group-size based prior probabilities of .32 and .68 for non-STEM and STEM groups, yielded 67.2% overall correct classification ($R = .22$, Wilks' *lambda* = .95, $\chi^2(4) = 13.12$, $p < .01$). Emotionality was the best predictor of group membership, with a canonical function loading of .91. Loadings of the remaining three scales ranged from .16 to .31. Thus, Hypothesis 3b was partially supported.

Table 6.10 College Major Group Differences on the Personality Scales and Factors

	STEM Group Mean	Non-STEM Group Mean	*T*
Scales			
Emotionality	4.23	4.56	-3.36**
Poise	3.95	3.85	1.12
Self-sufficiency	3.81	3.75	0.84
Toughness	4.07	4.02	0.60
Intellectance-1	4.23	4.24	-0.09
Intellectance-2	4.37	4.36	0.14
Creativity-1	4.26	4.30	-0.36
Creativity-2	4.61	4.60	0.06
Achievement-1	4.47	4.48	-0.16
Achievement-2	4.72	4.79	-0.69
Achievement-3	4.02	4.05	0.16
Planfulness-2	4.47	4.33	1.55
Judgment	4.60	4.46	1.73
Planfulness-1	3.79	3.86	-0.75
Dutifulness	4.05	3.90	1.20
Risk-avoidance	3.39	3.49	-0.87
Factors			
Toughmindedness	0.07	-0.16	1.77
Cognitively-oriented behavior	0.00	0.01	-0.07
Achievement	0.01	-0.02	0.25
Control	0.02	-0.04	0.42
Neuroticism	2.83	2.95	-1.08
Openness to Experience	4.20	4.47	-2.75
Conscientiousness	4.12	4.18	-0.56

Notes. Toughmindedness, cognitively-oriented behavior, achievement, and control are standardized variables. ** $p < .01$.

Hypotheses 4, 5, and 6 were related to the proposed personality factor associations with the science/math trait complex marker variables pertaining to vocational interests, self-concept measures, and cognitive abilities. Correlational results are presented in Table 6.11.

None of the hypothesized personality factors showed a pattern of associations in which they converged only with the realistic and investigative interests and were discriminated from the remaining four interest themes. Toughmindedness had small significant correlations with realistic (*r* = .13), enterprising (*r* = .14), and conventional (*r* = .13) interests. Cognitively-oriented behavior had small significant correlations with all the RIASEC interest themes (*r* range = .13 to .27) except for conventional interests. Achievement had small significant correlations with all themes (*r* range = .13 to .22) except for artistic interests. Control had a small positive correlation with conventional interests (*r* = .25) and a negative correlation with artistic interests (*r* = -.17). Thus, Hypothesis 4 was not supported.

For comparison purposes, the way in which the corresponding Big Five factors correlated with interests is also presented in Table 6.11. Like toughmindedness, neuroticism had non-significant associations with interests, with the exception of a negative association with social interests (*r* = -.15). The Big Five openness to experience factor correlated positively with the same variables as did cognitively-oriented behavior, but with larger correlations (*r* range = .17 to .55). A notable association was observed between openness to experience and artistic interests (*r* = .55). The Big Five conscientiousness factor, like achievement, had small significant correlations with all interests (*r* range = .15 to .26) except for artistic interests.

According to Hypothesis 5, moderate associations with the science, math, and spatial self-concepts, and a small association with the verbal self-concept, were expected. As expected, toughmindedness was significantly and moderately associated with math, science, and spatial self-concept (*r* range = .33 to .41), and associated to a lesser extent with verbal self-concept (r = .27). Cognitively-oriented behavior was mostly associated with verbal self-concept (r = .52), but it also had significant moderate associations with science (r = .38) and spatial self-concept (r = .40), and a small significant association with math self-concept (r = .18). Achievement had significant small correlations (r range = .14 to .25) with all four self-concept domains. Control had small significant associations with math (r = .20) and science self-concept (r = .12). The expected direction and magnitude of associations were observed only for toughmindedness; therefore, Hypothesis 5 was partially supported. Neuroticism, toughmindedness' correlate, showed smaller associations with self-concept (r range = -.13 to -.25).

According to Hypothesis 6, the proposed personality factors were expected to show moderate correlations with math and spatial abilities (see Table 6.11). The only significant association between the science/math trait complex-related abilities and personality was between ETS math abilities and toughmindedness (r = .18). Big Five neuroticism had non-significant associations with cognitive abilities. Cognitively-oriented behavior showed significant small to moderate associations only with verbal abilities (r = .33 with SAT Verbal and r = .28 with ETS Verbal). Openness to experience had a small significant correlation with SAT Verbal (r = .21) and a significant negative correlation with ETS math scores (r = -.20). The achievement and control factors were not associated with cognitive abilities. Thus, Hypothesis 6 was not supported.

Table 6.11 Personality Correlations with sInterests, Self-concept, and Abilities

	Hypothesized Personality Factors				Big Five Correlates		
	TM	COB	ACH	C	Neurot.	Openness	Consc.
Vocational Interest Themes							
Realistic	.13*	.20**	.13*	.05	-.09	.17**	.15*
Investigative	.07	.21**	.19**	.08	.00	.29**	.18**
Artistic	-.05	.27**	.06	-.17**	.06	.55**	.02
Social	.09	.25**	.22**	.01	-.15*	.32**	.26**
Enterprising	.14*	.13*	.16**	.06	-.10	.08	.18**
Conventional	.13*	-.04	.14*	.25**	.08	-.17**	.19**
Self-concept							
Math	.38**	.18**	.15*	.20**	-.25**	-.11	.12*
Science	.41**	.38**	.25**	.12*	-.18**	.10	.20**
Spatial	.33**	.40**	.14*	-.02	-.13*	.25**	.13*
Verbal	.27**	.52**	.16**	.02	-.15*	.38**	.16**
Cognitive Abilites							
SAT Math	.10	.08	-.04	-.01	-.10	-.06	-.09
SAT Verbal	.13	.33**	.03	-.06	-.06	.21**	-.03
ETS Math	.18*	.07	-.06	.05	-.09	-.20**	-.06
ETS Spatial	.10	.12	-.04	-.02	-.07	-.04	-.07
ETS Verbal	.10	.28**	.13	.17*	-.07	.06	.17*

Notes. TM: Toughmindedness, COB: Cognitively-oriented behavior, ACH: Achievement, C: Control, Neurot: Big Five Neuroticims, Openness: Big Five Openness to Experience, Consc: Big Five Conscientiousness, ETS: Educational Testing Service. * $p < .05$; ** $p < .01$.

6.1.4 Exploration of Personality and STEM Vocational Criteria Associations

Data on several variables related to STEM attachment and achievement were also collected in Study 1 in order to make preliminary explorations as to their associations with the newly developed STEM Interest Complexity scales. Even though not hypothesized, the personality factor associations with these STEM-related vocational criteria were also explored in order to gain a more holistic understanding of the hypothesized variables' relation to STEM fields. These STEM attachment and achievement-related criteria were: STEM membership, self-reported intentions to persist in and further pursue a STEM field (specifically, getting a BS degree, a graduate degree, and pursuing a career), the number of math and science courses taken in high school, math/science competition/club participation in high school and college, the age at which the participant decided to pursue a STEM field, STEM-related course Grade Point Average (GPA), and Cumulative Grade Point Average (CGPA).

First the psychometric properties of the newly developed measure, which assesses intentions to persist in and further pursue STEM fields, are presented. Then, descriptive statistics for the vocational criteria are presented, followed by correlation analyses to explore their associations with the personality variables.

6.1.4.1 Psychometric Properties of the Scale Assessing Intentions to Persist in STEM

The scale assessing STEM major students' self-reported intentions to persist in a STEM-related field was newly developed for the present study. A total of 12 items were administered, rated on a 6-point Likert type scale. Parallel analyses suggested four factors. A PAF with Oblique rotation was performed on the 12 items, extracting four factors. The unrotated factor solution explained 68.3% of variance. The first factor with four items was related to intentions to further pursue a career in a STEM area. The second factor with two items was related to intentions to take STEM courses the following year. The third factor with three items was related to intentions to pursue a graduate degree in a STEM field. Finally, the fourth factor with three items was related to intentions to persist in a STEM major to get a BS degree. Cronbach alpha internal consistency reliabilities were .88, .85, .79, and .82, respectively. Descriptive statistics of the factors are shown in Table 6.12.

Among STEM majors, intentions to pursue a STEM BS, graduate degree and career were significantly associated with STEM-area GPA (rs = .34, .27, and .24, respectively) and with the Big Five conscientiousness factor (rs = .15, .16, and .24, respectively). These intentions were also significantly associated with math and science self-concept (r range = .27 to .32). Graduate degree and career intentions were significantly associated with high school and college math/science club participation (r = .20 and r = .23). STEM career intentions were associated with realistic interests (r = .20), and graduate degree intentions were associated with investigative interests (r = .23). The fourth factor related to intentions to take STEM-related courses the next year was not associated with any of the aforementioned variables, and therefore was not included in further analyses.

6.1.4.2 Descriptive Statistics for Vocational Criteria

Means, standard deviations, ranges, and skewness for the vocational criteria are presented in Table 6.12. College achievement indices of objectively obtained CGPA and STEM-related course GPA (calculated by determining the STEM quality points divided by total STEM hours) were negatively skewed. Intentions to persist in a STEM BS and to further pursue a STEM career, as well as the age when the participant decided to pursue a STEM field were also negatively skewed. Participants who decided to pursue a STEM field before the age of 10 were deleted from analyses (14 cases were deleted). The number of math and science courses taken in high school was positively skewed. Percentage of participants endorsing the categorical criteria is presented in Table 6.13. Vocational criteria intercorrelations are presented in Table J.3.

Table 6.12 Decriptive Statistics of Vocational Criteria

	N	M	Sd	Range	Skewness
GPA	171	3.00	0.67	3.39	-0.80
STEM GPA	166	2.74	0.89	4.00	-0.75
Intentions to pursue STEM BS	184	5.16	0.96	5.00	-1.73
Intentions to pursue STEM grad degree	184	3.75	1.32	5.00	-0.22
Intentions to pursue STEM career	184	4.54	1.17	5.00	-0.85
# of high school math courses	264	4.50	0.86	6.00	1.65
# of high school science courses	264	4.63	1.39	9.00	1.73
Age decided to purse STEM	186	15.29	2.41	9.00	-0.64

Notes. Standard error of skewness for variables ranges between .15 and .19. GPA: Grade Point Average; STEM: Science, Technology, Engineering, and Mathematics; BS: Bachelor of Science; Grad: Graduate.

Table 6.13 Frequencies of the Categorical Vocational Criteria

	N	%
STEM membership		
Non-STEM	87	31.8
STEM	187	68.2
High school STEM competition participation		
No	150	54.7
Yes	122	44.5
High cchool STEM club participation		
No	149	54.5
Yes	125	45.6
College STEM activity participation		
No	244	89.1
Yes	28	10.2

Notes. High school STEM competition participation, high school STEM club participation, and college STEM activity participation: 0 = No, I haven't participated, 1 = Yes I participated. STEM: Science, Technology, Engineering, and Mathematics.

6.1.4.3 Personality and Vocational Criteria Associations

Exploratory testing was carried out investigating the associations between the proposed personality factor composites and the aforementioned vocational criteria. All correlations are presented in Table 6.14, as are the Big Five personality factors.

Table 6.14 Personality Factor Associations with STEM-related Vocational Criteria

	Hypothesized Personality Factors				Big Five Correlates		
	TM	COB	ACH	C	Neurot.	Openness	Consc.
GPA	.01	.00	.28**	.32**	-.01	-.06	.18*
STEM GPA	-.02	-.05	.24**	.32**	.07	-.14	.14
STEM Membership	.11	.00	.02	.03	-.07	-.17**	-.03
STEM BS Intentions	.11	.10	.19**	.17*	.00	-.02	.15*
STEM Grad Degree Intentions	.04	.25**	.16*	.00	-.01	.16*	.16*
STEM Career Intentions	.22**	.23**	.27**	.15*	-.11	.04	.24**
# of High School Math Courses	-.01	.02	.08	.13*	.04	-.05	.07
# of High School Science Courses	.03	.09	.01	.04	.06	.04	.04
High School Stem Competition Part	.05	.27**	.04	.03	.06	.22*	.01
High School Stem Club Participation	.03	.16**	.00	.07	.12*	.05	.05
College STEM Activity Part	.09	.15*	-.04	-.03	-.04	.15*	.05
Age decided to pursue STEM	-.04	-.14	-.05	-.10	-.17*	-.11	-.03

Notes. High school STEM competition participation, high school STEM club participation, and college STEM activity participation have been coded as 0 = No, haven't participated, 1 = Yes I participated. TM: Toughmindedness; COB: Cognitively-oriented behavior; ACH: Achievement; C: Control; Neurot: Big Five Neuroticism; Openness: Big Five Openness to Experience; Consc: Big Five Conscientiousness; GPA: Grade Point Average; STEM: STEM: Science, Technology, Engineering, and Math; BS: Bachelor of Science; Grad: Graduate; Part: Participation. * $p < .05$; ** $p < .01$.

Toughmindedness had a significant association with intentions to pursue a STEM career (r = .22). No other STEM criterion was associated with toughmindedness.

Cognitively-oriented behavior had small significant associations with STEM high school/college competition/club participation, and with intentions to pursue a STEM graduate degree and career (r range = .15 to .27). Openness to experience also had small significant associations with several of the criteria, but the pattern of relationship was less consistent across the variables, with slightly lower correlations ($|r|$ range = .15 to .22).

The achievement factor had significant small correlations with the age at which the participant decided to pursue STEM and with intentions to persist in a STEM field ($|r|$range = .16 to .27). Conscientiousness was also significantly associated with the same variables, but with slightly lower correlations (r range = .15 to .24).

Control correlated with intentions to get a STEM BS degree, intentions to pursue a STEM career, and the number of math courses taken in high school (r range = .13 to .17). Significant and moderate associations were observed between the achievement and control factors and the achievement indices of GPA and STEM-GPA (r range = .24 to .32). Conscientiousness had a small significant correlation only with CGPA (r = .18).

6.2 Preliminary Findings for the STEM Interest Complexity Scales

Analyses were based on the Study 1 sample of 274 undergraduates, of which 184 were in a STEM-related major, 185 completed cognitive ability measures from the ETS-Kit, and 166 granted permission to access their transcripts (which were used to calculate STEM-related GPA).

6.2.1 Exploratory Factor Analysis

Items were summed to form scales correspondingto the DOT complexity levels (e.g. numerical copying, analyzing etc). In order to determine the number of factors, a parallel analysis was performed based on 28 scales. Comparison of the random and real data-generated eigenvalues indicated four factors (see Figure 6.2). The 28 scales, which spanned the four content domains of involvement with numerical, symbolic, spatial data, and ideas, were subjected to PAF with Oblique rotation. The unrotated 4-factor solution explained 74% of variance. Scales within a content all loaded together, forming four factors interpreted as the numeric, symbolic, spatial, and ideas domains (see Table 6.15).

Complexity levels of scales were theoretically determined based on the DOT data complexity levels and the underlying characteristics of the tasks, which span low, moderate, and high complexity occupations. Therefore, within each content domain, low, moderate, and high complexity scales were formed by summing the items that corresponded to each complexity level. Descriptive statistics of these scales are presented in Table 6.16 and intercorrelations in Table 6.17.

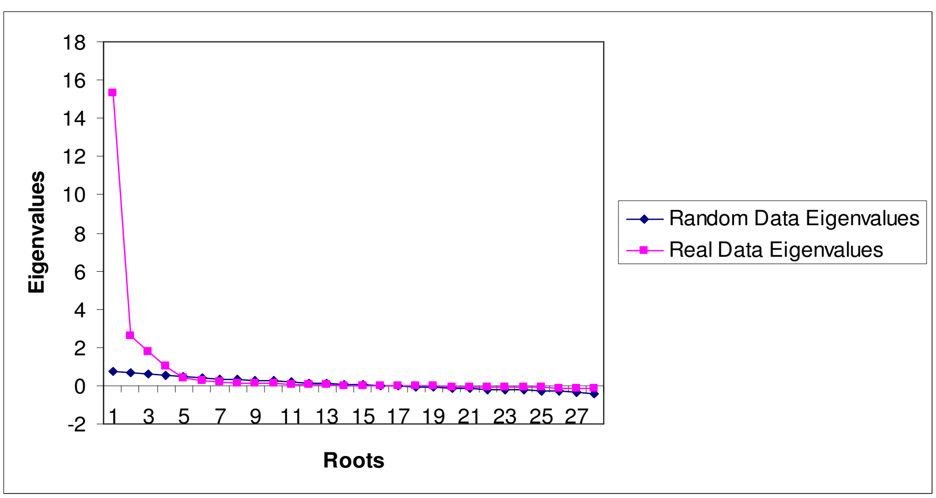

Figure 6.2 Parallel Analysis for Determining the Number of STEM Interest Factors

Table 6.15 EFA for the STEM Interest Complexity Factors

	I	III	III	IV	h^2
Symbolic Compute MOD	**.905**	.071	-.021	-.003	.894
Symbolic Learning LOW	**.835**	.087	.007	.035	.797
Symbolic Generate HIGH	**.829**	.032	-.197	-.066	.860
Symbolic Analyze MOD	**.754**	.013	-.109	.117	.823
Symbolic Synthesize HIGH	**.710**	.095	-.122	.094	.805
Symbolic Compile MOD	**.676**	.007	.050	.205	.633
Symbolic Compare LOW	**.668**	.034	-.075	.126	.665
Symbolic Copy LOW	.327	.024	-.071	.345	.440
Spatial Generate HIGH	.209	**.867**	-.070	-.162	.882
Spatial Analyze MOD	.231	**.781**	-.123	-.067	.888
Spatial Compute MOD	.134	**.767**	-.061	.077	.824
Spatial Compare LOW	-.097	**.755**	-.043	.243	.772
Spatial Synthesize HIGH	.075	**.733**	-.111	.086	.744
Spatial Copy LOW	-.123	**.724**	.071	.-.005	.431
Ideas Compile MOD	-.074	-.057	**-.939**	.038	.789
Ideas Synthesize HIGH	-.005	.002	**-.936**	.067	.941
Ideas Generate HIGH	.022	.124	**-.916**	-.050	.905
Ideas Compare LOW	-.003	-.019	**-.915**	-.023	.795
Ideas Analyze MOD	.085	.002	**-.881**	.038	.910
Ideas Solving MOD	.124	.060	**-.771**	-.014	.763
Numerical Compare LOW	-.003	.055	.037	**.791**	.631
Numerical Simple Compute LOW	.039	.054	-.041	**.728**	.641
Numerical Compute MOD	.216	-.023	-.089	**.727**	.849
Numerical Compile MOD	.214	.019	.018	**.704**	.729
Numerical Synthesize HIGH	.348	.052	-.064	**.572**	.813
Numerical Difficult Compute HIGH	.305	.011	-.018	**.539**	.616
Numerical Analyze MOD	.358	.014	-.080	**.496**	.690
Numerical Copy LOW	-.083	.038	-.077	.352	.133

Notes. Values with a factor loading higher than .40 are shown in bold type. LOW: Low complexity, MOD: Moderate-complexity, HIGH: High-complexity.

6.2.2 Descriptive Statistics and Scale Reliabilities

Descriptive statistics and internal consistency reliabilities are presented in Table 6.16. Numerical, symbolic, and spatial moderate- and high-complexity scales had a relatively normal distribution of scores. Numeric and symbolic low-complexity scales were negatively skewed. For ideas and General STEM Interests, all complexity level scales were negatively skewed. Means of the low-complexity scales were higher than the means of the moderate and high-complexity scales (except for the ideas domain). High- and moderate-complexity scale means were closer to each other. Unit-weighted z-score composites of the moderate- and high-complexity scales were formed for each domain.

STEM Interest Complexity scales had good internal consistency reliabilities, ranging from .72 to .96. Several items had item-total correlations lower than .40: Numeric low-complexity item ("I dislike it when I need to copy down long numbers"); numeric moderate-complexity item ("When the solution to a numeric problem turns out to be incorrect, I don't like going back to check the numbers and re-analyze it"); symbolic moderate-complexity item ("I prefer to follow conceptual relations in narrative form as opposed to in symbolic formulas"); spatial low-complexity item ("I find it fun to try reading something upside down"); and ideas moderate-complexity item ("For the troubleshooting of an equipment or technological simulation in a STEM area, I don't like looking for relevant ideas in different sources; e.g., text books, magazines, articles"). For Study 2, the numeric and ideas moderate-complexity items, which were reverse-coded with negations (i.e. don't like), were re-worded by dropping the negation.

Table 6.16 Study 1 Descriptive Statistics for the STEM Interest Complexity Scales

Scale	# of items	Mean	Sd	Range	Skewness	Cronbach's α
Numeric Low	7	4.05	0.87	5.00	-0.64	.82
Numeric Mod	13	3.61	0.89	5.00	-0.21	.91
Numeric High	8	3.53	0.95	4.88	-0.25	.87
Symbolic Low	4	3.68	0.98	5	-0.41	.77
Symbolic Mod	16	3.29	1.00	5	-0.12	.95
Symbolic High	10	3.33	1.01	5	-0.07	.93
Spatial Low	7	3.75	0.83	5	-0.30	.76
Spatial Mod	9	3.51	1.00	5	-0.34	.91
Spatial High	8	3.48	1.09	5	-0.21	.93
Ideas Low	2	3.66	1.10	5	-0.54	.72
Ideas Mod	11	3.59	1.00	5	-0.41	.94
Ideas High	17	3.77	1.00	5	-0.53	.96
General Low	3	4.12	1.06	5	-0.80	.81
General Mod	8	3.66	1.03	5	-0.47	.93
General High	4	3.59	1.20	5	-0.37	.90

Note. All scales were rated on a 6-point scale. Standard error of skewness is 0.15. Low: Low-complexity; Mod: Moderate-complexity; High: High-complexity.

Table 6.17 Intercorrelations between STEM Interest Complexity Scales

	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1. N L	1.0													
2. N M	.81	1.0												
3. N H	.77	.91	1.0											
4. Sy L	.67	.71	.72	1.0										
5. Sy M	.59	.78	.80	.79	1.0									
6. Sy H	.58	.76	.77	.76	.93	1.0								
7. Sp L	.45	.39	.41	.41	.37	.38	1.0							
8. Sp M	.49	.58	.59	.53	.61	.64	.79	1.0						
9. Sp H	.42	.49	.50	.49	.54	.59	.79	.93	1.0					
10. I L	.38	.51	.52	.46	.52	.58	.37	.56	.51	1.0				
11. I M	.50	.59	.59	.57	.62	.68	.44	.63	.58	.87	1.0			
12. I H	.50	.57	.56	.55	.59	.67	.49	.65	.62	.86	.96	1.0		
13. G L	.38	.37	.37	.39	.35	.43	.43	.50	.46	.62	.70	.72	1.0	
14. G M	.48	.56	.55	.55	.60	.67	.40	.60	.54	.76	.85	.84	.81	1.0
15. G H	.44	.54	.53	.54	.61	.67	.38	.58	.55	.72	.84	.84	.73	.89

Notes. N: Numeric, Sy: Symbolic, Sp: Spatial, I: Ideas, G: General STEM Interest Complexity, L: Low-complexity, M: Moderate-complexity, H: High-complexity. All correlations are significant at the alpha .001 level.

6.2.3 STEM Interest Complexity Associations with Constructs and Criteria

Pilot testing the newly-developed STEM Interest Complexity Measure involved exploring the construct validity based on the measure's associations with traditional interest assessments (i.e. Holland interests, self-concept) and cognitive abilities, and exploring the concurrent criterion-related validity based on the measure's associations with vocational criteria. Descriptive statistics for the moderate- and high-complexity numeric, symbolic, spatial, ideas, and general STEM interest scales are presented in Table 6.18.

Table 6.18 Descriptives for STEM Interest Complexity Domain Composites

	Mean	Std	Range	Skewness
Numeric	0	1.00	5.38	-.22
Symbolic	0	1.00	5.07	-.10
Spatial	0	1.00	4.90	-.29
Ideas	0	1.00	5.06	-.47
General	0	1.00	4.65	-.44
Interest Complexity Composite (Numeric+Symbolic+Ideas)	0	1.00	5.61	-.29

Notes. Variables are standardized as z-scores. Each domain composite was formed based on the moderate- and high-complexity scales. Standard error or skewness is .15.

6.2.3.1 Associations with Traditional Interest Assessments, Abilities, and Personality

Analyses were conducted using the moderate- and high-complexity composite for each content factor. The STEM Interest Complexity scales were first correlated with the traditional interest assessments (i.e. relevant Holland interest themes and self-concept scales). All correlations are presented in Table 6.19. Scales had significant moderate associations with realistic interests (*r* range = .36 to .62), significant small to moderate associations with investigative interests (*r* range = .19 to .50), and small to moderate associations with conventional interests (*r* range = .22 to .47). The highest correlations were observed between the spatial scale and realistic interests (*r* = .62), between the ideas scale and investigative interests (*r* = .50), and between the numeric scale and conventional interests (*r* = .47). The STEM Interest Complexity scales showed moderate to strong associations with math self-concept (*r* range = .42 to .68), science self-concept (*r* range = .38 to .72), and spatial self-concept (*r* range = .32 to .63). Verbal self-concept did not correlate with the STEM Interest Complexity scales, except for a small significant negative correlation with symbolic interest complexity (*r* = -.13).

STEM Interest Complexity scales were also correlated with cognitive ability measures (see Table 6.19). SAT Math scores significantly moderately correlated with all complexity scales (*r* range = .35 to .48) and ETS Kit Math ability significantly moderately correlated with numeric (*r* = .43) and symbolic interest complexity (*r* = .35). ETS Kit Math ability also had significant small correlations with idea complexity (*r* = .19) and general STEM interest complexity (*r* = .24). ETS Kit Spatial ability had a significant moderate correlation with spatial interest complexity (*r* = .34) and significant small correlations with the other complexity scales (*r* range = .19 to .25). Verbal abilities did not significantly correlate with any of the STEM Interest Complexity scales.

Finally, STEM Interest Complexity scales were correlated with personality factors (see Table 6.19). STEM Interest Complexity scales had significant moderate associations with toughmindedness (*r* range = .26 to .35) except for a small correlation with spatial interests. The toughmindedness factor's Big Five correlate neuroticism also showed significant, but smaller, associations. Associations with cognitively-oriented behavior were small to moderate (r range = .23 to .34). Achievement had small significant associations with all scales except for symbolic interests. Control had small significant correlations only with the numeric and idea scales. Neither openness to experience nor conscientiousness had consistent significant associations with interest complexity.

Table 6.19 STEM Interest Complexity Associations with Traditional Interest Assessments, Cognitive Abilities, and Personality

	Numeric	Symbolic	Spatial	Ideas	General
Vocational Interests					
Realistic	.36**	.38**	.62**	.49**	.43**
Investigative	.19**	.21**	.28**	.50**	.49**
Artistic	-.12*	-.07	.12*	.00	-.03
Social	.09	.04	.14*	.19*	.15*
Enterprising	.09	.01	.03	.07	.09
Conventional	.47**	.35**	.22**	.29**	.24**
Self-evaluations					
Math self-concept	.68**	.67**	.42**	.50**	.54**
Science self-concept	.46**	.50**	.38**	.67**	.72**
Spatial self-concept	.34**	.32**	.63**	.42**	.37**
Verbal self-concept	-.11	-.13*	-.08	.07	.04
Cognitive abilities					
SAT Math	.45**	.48**	.35**	.37**	.38**
ETS Math	.43**	.35**	.11	.19*	.24**
ETS Spatial	.24**	.25**	.34**	.25**	.19*
ETS Verbal	.12	.06	.06	.00	-.02
SAT Verbal	.02	.04	-.04	.13	.13
Personality					
Toughmindedness	.33**	.26**	.18*	.35**	.30**
Cognitive behavior	.23**	.23**	.28**	.34**	.33**
Achievement	.15*	.08	.12*	.21*	.18*
Control	.19*	.10	.05	.12*	.07
Neuroticism	-.20**	-.17**	-.14*	-.22**	-.19**
Openness to Experience	-.05	-.07	.15*	.09	.10
Conscientiousness	.12*	.06	.11	.20**	.14**

Notes. Correlations with the self-report measures of Holland themes, self-evaluations, personality, and self-reported SAT scores are based on a sample size of 274, correlations with the ETS ability factors are based on a sample size of 185. ETS: Educational Testing Service. * $p < .05$; ** $p < .01$.

6.2.3.2 Associations with STEM Vocational Criteria

STEM Interest Complexity associations with achievement in and attachment to STEM fields were explored. Correlations between interest complexity scales and vocational criteria are presented in Table 6.20. All correlations were run for the entire sample (N = 274) and for STEM participants (N = 184). Results indicated that among STEM majors, the STEM Interest Complexity scales had small to moderate associations (r range = .03 to .44) with college achievement in STEM majors and with variables indicating an attachment to STEM areas. The highest associations were observed for moderate- and high-complexity symbolic interests and ideas, followed by moderate- and high-complexity numeric interests.

Within the STEM major sample, STEM-GPA had significant small associations with moderate- and high-complexity numeric interests (r = .20 and r = .25), and significant moderate associations with moderate and high-complexity symbolic interests (r = .35 and r = .32). Correlations with the low-complexity scales were non-significant, except for a small significant correlation with symbolic interests. STEM-GPA did not correlate significantly with the ideas or spatial scales. Experiential variables indicating an attachment to STEM areas had small but mostly significant associations with moderate and high-complexity scales, with significant correlations ranging from magnitudes of .16 to those of .29. Intentions to persist in and further pursue a STEM-related field (for a BS, a graduate degree, and a career) were significantly associated with STEM Interest Complexity, with significant correlations ranging from .15 to .44. For the numeric and spatial interest scales, low-complexity interests were less associated with intentions to persist than were moderate- and high-complexity interests.

Table 6.20 STEM Interest Complexity Associations with STEM Vocational Criteria

Measures	STEM GPA	STEM BS Degree Intent	STEM Grad Degree Intent	STEM Career Intent	Age in which decided to enter STEM	# of High School Science Course	High School STEM Comp-etition	High School STEM Club Particip
Numeric Low								
Stem major	.09	.22**	.04	.20**	.03	.04	.12	.03
All sample	.19*					.15*	.13*	.10
Numeric Mod								
Stem major	.20*	.32**	.21**	.29**	-.16*	.11	.22**	.11
All sample	.27**					.21**	.20**	.19**
Numeric High								
Stem major	.25**	.31**	.25**	.33**	-.15*	.10	.24**	.17*
All sample	.31**					.21**	.22**	.21**
Symbolic Low								
Stem major	.19*	.34**	.27**	.40**	.08	.12	.29**	.22**
All sample	.25**					.20**	.25**	.24**
Symbolic Mod								
Stem major	.35**	.38**	.34**	.41**	-.18*	.19**	.24**	.25**
All sample	.38**					.26**	.24**	.32**
Symbol High								
Stem major	.32**	.32**	.35**	.39**	-.19*	.21**	.25**	.29**
All sample	.34**					.27**	.23**	.33**
Spatial Low								
Stem major	-.07	.15*	.13	.18*	-.12	.13	.20**	.17*
All sample	-.06					.18**	.21**	.14*
Spatial Mod								
Stem major	.09	.17*	.24**	.31**	-.20**	.17*	.25**	.23**
All sample	.11					.24**	.25**	.20**
Spatial High								
Stem major	.03	.10	.22**	.25**	-.18*	.14	.19**	.22**
All sample	.03					.22**	.20**	.18**
Ideas Low								
Stem major	.12	.24**	.31**	.37**	-.20**	.13	.17*	.14
All sample	.17*					.22**	.19**	.22**
Ideas Mod								
Stem major	.17	.31**	.38**	.44**	-.22**	.14	.22**	.21**
All sample	.25**					.26**	.23**	.29**
Ideas High								
Stem major	.10	.29**	.35**	.43**	-.23**	.16*	.19**	.21**
All sample	.20**					.25**	.21**	.28**

Notes. Low: Low-complexity scale, Mod: Moderate-complexity scale, High: High-complexity scale, STEM: Science, Technology, Engineering, Mathematics. For correlations based on STEM major participants, sample size ranges between 112 and 184. For correlations based on participants from all majors, sample size ranges between 119 and 259. Scale points range between 1 = very untrue of me, 6 = very true of me. * $p < .05$; ** $p < .01$.

I also performed hierarchical regression analyses to explore how much variance the STEM Interest Complexity scales would add over the traditional forms of interest assessment. STEM-GPA and the three factors relating to intentions to persist in and pursue a STEM field were entered as criteria. In the first step, realistic and investigative interests were entered as predictors. Math and science self-concept were entered as predictors in the second step. Finally, in the third step, a composite of the moderate- and high-complexity STEM Interest Complexity domains was entered as the predictor. Unit-weighted z-scores of scales were summed to form the composite and then the composite was re-standardized. Spatial interest complexity scales were not included in the composite as they showed lower associations with the criteria. Analyses were carried out within the STEM sample of participants.

All four Hierarchical Regression analyses indicated that the STEM Interest Complexity composite was significant at the end of the third step, and added between 5% and 10% incremental variance over and above the two Holland interests and self-concept measures (see Table 6.21). Only STEM Interest Complexity significantly predicted all criteria, with Beta weights ranging from .36 to .46.

6.2.3.3 Predicting Major Choice from STEM Interest Complexity

A direct discriminant function analysis was performed by entering the four STEM Interest Complexity domains (composites of moderate- and high-complexity scales) as predictors of major membership (STEM versus non-STEM membership). A significant association between predictors and group membership was found (Wilk's *lambda* = .73, $\chi^2(4) = 85.79$, $p < .01$), in which the STEM Interest Complexity scales accounted for 27% of variance between groups. Overall, 76.6% of cases were correctly classified; 91%

of STEM (prior probability = .68) and 46% of non-STEM (prior probability = .32) participants were classified correctly. Holland's six interest themes had a 77% correct classification rate. However, the variance explained by the six interest themes was 14%.

Table 6.21 Prediction of STEM Criteria based on Vocational Interest Measures

Dependant Variable	STEM GPA	STEM BS Intentions	STEM Grad degree Intentions	STEM Career Intentions
Step 1				
1. Realistic Interests	-.07	-.08	.00	.19*
2. Investigative Interests	.02	.17	.23**	.02
R^2	**.00**	**.02**	**.05**	**.04**
F	.23	1.91	4.86**	3.94*
df	(2,117)	(2,181)	(2,181)	(2,181)
Step 2				
3. Realistic Interests	-.11	-.14	-.04	.13
4. Investigative Interests	.02	.13	.13	-.05
5. Math self-concept	.23	.24**	.00	.19*
6. Science self-concept	-.06	.14	.25*	.20*
R^2_{change}	**.05**	**.10**	**.05**	**.10**
F_{change}	3.03	10.62**	4.94**	10.55**
df	(2,115)	(2,179)	(2,179)	(2,179)
Step 3				
7. Realistic Interests	-.18	-.26**	-.19*	.01
8. Investigative Interests	.05	.13	.13	-.05
9. Math self-concept	.01	.04	-.24*	-.02
10. Science self-concept	-.06	.09	.19*	.15
11. STEM Interest Complexity	.36**	.39**	.46**	.39**
R^2_{change}	**.05**	**.08**	**.10**	**.08**
F_{change}	6.69**	16.59**	23.31**	17.03**
df	(1,114)	(1,178)	(1,178)	(1,178)

Note. Values in table are Beta weights, unless otherwise indicated. Percent of incremental variance is shown in bold type. STEM: Science, Technology, Engineering, and Mathematics.
* $p < .05$; ** $p < .01$.

6.3 Exploration of the Trait Complex Structure

The main objective of the present study is to investigate the personality and interest correlates of the science/math trait complex. At this point, it is necessary to analyze the trait complex structure, including personality factors and STEM interest complexity, to gain a more holistic perspective on the science/math trait complex.

Exploratory factor analyses using PAF with Oblique rotation were run to explore the trait complex structure. First, a parallel analysis was performed on the variables in this study in order to identify the number of factors underlying the trait complex structure. A total of 19 variables were entered into the analysis: realistic, investigative, and artistic interests; math, science, spatial, and verbal self-concept scales; the toughmindedness, cognitively-oriented behavior, achievement, and control personality factors; the Big Five openness to experience and neuroticism factors; the ETS Kit math, spatial, and verbal ability factors; SAT Math and SAT Verbal scores; and the STEM interest complexity composite. Variable intercorrelations are presented in Table 6.22.

Parallel analysis suggested five factors, with five roots clearly having real data eigenvalues larger than the random data generated eigenvalues (see Figure 6.3). However, a PAF analysis with Oblique rotation did not give a 5-factor solution (due to variable communalities exceeding 1). A 4-factor solution was extracted, which yielded two factors based on methods variance (a math ability factor and a personality factor). Buja and Eyuboglu (1992) remarked on the necessity of exploring the nature of factors, as parallel analysis can yield more factors than warranted. Following this advice, 3-factor and 2-factor solutions were also obtained, which yielded meaningful factors.

Table 6.22 Intercorrelations between Variables forming Trait Complexes

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
1. Realistic interests	1.000																	
2.Investigative interests	.497	1.000																
3. Math self-concept	.225	.159	1.000															
4. Science self-concept	.354	.501	.633	1.000														
5. Spatial self-concept	.487	.249	.459	.495	1.000													
6. Verbal self-concept	.013	.209	.033	.207	.247	1.000												
7. Artistic interests	.318	.280	-.172	-.027	.176	.328	1.000											
8. Cognitive behavior	.199	.211	.180	.382	.400	.517	.271	1.000										
9. Tough-mindedness	.132	.069	.382	.409	.329	.270	-.047	.550	1.000									
10.Achievement	.132	.191	.151	.247	.137	.163	.058	.335	.321	1.000								
11. Control	.049	.075	.199	.122	-.021	.022	-.168	.007	.054	.557	1.000							
12. ETS Math abilities	-.024	-.032	.315	.196	.043	.062	-.161	.073	.183	-.058	.047	1.000						
13.ETS Verbal abilities	.001	.089	.020	.080	.052	.375	.127	.280	.192	.130	.170	.344	1.000					
14.ETS Spatial abilities	.208	.106	.240	.174	.336	-.051	-.028	.115	.101	-.044	-.017	.305	.120	1.000				
15.SAT Verbal	-.054	.090	-.013	.096	-.123	.389	.070	.326	.125	.034	-.059	.242	.418	-.139	1.000			
16. SAT Math	.150	.027	.440	.262	.161	-.145	-.149	.077	.097	-.039	-.009	.507	.073	.244	.293	1.000		
17. Interest Complexity	.459	.336	.692	.610	.405	-.063	-.072	.299	.351	.163	.154	.361	.070	.272	.072	.481	1.000	
18. Openness to experience	.171	.285	-.113	.099	.249	.384	.545	.552	.051	.036	-.204	-.204	.063	-.036	.208	-.058	-.008	1.000
19Neuroticism	-.094	-.002	-.247	-.181	-.126	-.145	.058	-.232	-.638	-.311	-.069	-.093	-.068	.074	-.055	-.097	-.221	.031

Notes. Sample sizes range between 185 and 274. Correlations larger than .12 are significant at .05 and correlations larger than .16 are significant at .01

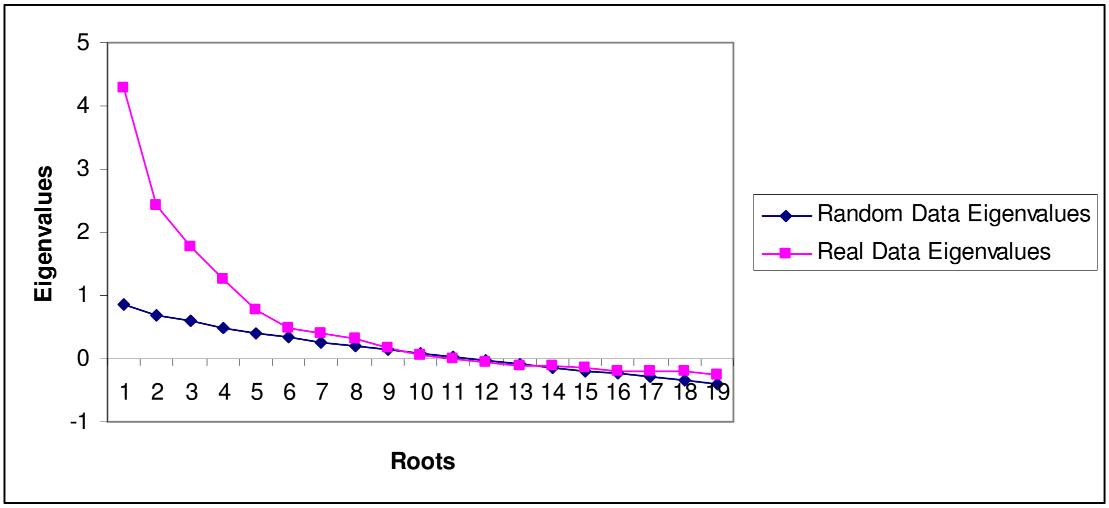

Figure 6.3 Parallel Analysis for Determining the Number of Trait Complex Factors

In the 3-factor solution, realistic interests, science self-concept, STEM interest complexity, spatial self-concept, math self-concept, investigative interests, and spatial ability loaded on the first factor. Achievement and spatial abilities also loaded on this factor, but with very small loadings. The first factor was interpreted as a science trait complex. Verbal self-concept, cognitively-oriented behavior, Big Five openness to experience, verbal ability, SAT Verbal scores, and artistic interests loaded on the second factor. This factor was interpreted as the intellectual/cultural trait complex. Math self-concept and STEM interest complexity with cross-loadings, toughmindedness, ETS Kit math ability, SAT Math, Big Five neuroticism, and science self-concept with a cross-loading loaded on the third factor. This factor was named as the math trait complex. The control personality factor also loaded on this factor, but with a small loading.

In the 2-factor solution the rotated factors were interpreted as the science/math and the intellectual/cultural trait complex. Factor loadings based on the pattern matrix are presented in Table 6.23. STEM interest complexity, math, science, and spatial self-concept, toughmindedness, SAT math scores, realistic interests, ETS Kit math abilities, investigative interests, achievement, neuroticism, control, and spatial abilities loaded on the science/math trait complex factor. Openness to experience, verbal self-concept, cognitively-oriented behavior, artistic interests, and verbal abilities loaded on the intellectual/cultural trait complex factor. Unit-weighted z-scores of the variables with loadings larger than .30 were summed to obtain trait complex composites.

The science/math trait complex composite was correlated with the vocational criteria. Correlations are presented in Table 6.24. Magnitude of significant associations was mostly moderate, ranging from .16 to .50.

Table 6.23 Two-factor Structure of the Trait Complexes

	I	II	h^2
I. Science/Math Trait Complex			
STEM Interest Complexity	**.905**	-.075	.801
Math Self-concept	**.865**	-.141	.727
Science Self-concept	**.739**	.166	.614
Spatial Self-concept	**.485**	**.347**	.412
Toughmindedness	**.482**	.149	.279
SAT Math	**.453**	-.131	.203
Realistic Interests	**.452**	.252	.306
ETS Kit Math Ability	**.398**	-.098	.155
Achievement	**.321**	.218	.174
Investigative Interests	**.320**	**.311**	.232
Neuroticism	**-.319**	.004	.101
Control	**.308**	-.047	.092
ETS Kit Spatial Ability	**.307**	-.024	.092
II. Intellectual/Cultural Trait Complex			
Openness to Experience	-.251	**.782**	.609
Verbal Self-concept	-.064	**.730**	.521
Cognitively-oriented Behavior	.203	**.642**	.497
Artistic Interests	-.169	**.620**	.378
ETS Kit Verbal Ability	.078	**.366**	.149
SAT Verbal	.019	**.324**	.108

Notes. Factor loadings of .30 and above are shown in bold type. STEM: Science, Technology, Engineering, and Mathematics; ETS: Educational Testing Service.

Table 6.24 Correlations of Science/Math Trait Complex with Vocational Criteria

	Science/Math Complex
STEM GPA	.35**
STEM Membership	.37**
STEM BS Intentions	.43**
STEM Graduate Degree Intentions	.41**
STEM Career Intentions	.50**
# of High School Math Courses	.16*
# of High School Science Courses	.26**
High School STEM Competition Participation	.24**
High School STEM Club Participation	.25**
College STEM Activity Participation	.20**
Age decided to pursue STEM	-.08

Notes. High school/college STEM activity participation: 0 = No, I haven't participated, 1 = Yes, participated. Sample sizes range from 104 to 146. STEM: Science, Technology, Engineering, and Mathematics; GPA: Grade Point Average; BS: Bachelor of Science. $^{*}p < .05$; $^{**}p < .01$.

6.3.1 Variance Ability and Non-Ability Composites Share with Criteria

Hierarchical regression analyses were performed on each vocational criterion to investigate whether the non-ability markers of the science/math trait complex added significant incremental variance over math abilities. The non-ability variables were combined to form a composite. SAT Math scores were entered in the first step of the regression analyses and the non-ability composite was entered in the second step.

Math ability significantly predicted STEM-GPA, STEM membership, and high school STEM competition and club participation. The non-ability composite added between 7% and 19% significant incremental variance over math abilities in the prediction of the intentions to pursue a STEM BS degree, graduate degree, and a career. The non-ability composite added between 2% and 5% significant incremental variance over math ability when STEM-GPA, STEM membership, number of high school science courses, and high school and college competition and club participation were entered as the dependent variables (see Table 6.25).

Table 6.25 Hierarchical Regression Analyses Predicting STEM Achievement and Attachment based on Math Ability and Non-Ability Markers

Dependant Variable	STEM GPA	STEM Member-Ship	STEM BS Intentions	STEM Grad degree Intentions	STEM Career Intentions	# of HS Science Courses	HS STEM Competi-tion Particip.	HS STEM Club Particip.	College STEM Activity Particip.
Step 1									
1. SAT Math	.36**	.39**	.10	.12	.07	.09	.19**	.26**	.10
R^2	**.13**	**.15**	**.01**	**.02**	**.01**	**.01**	**.04**	**.07**	**.01**
F	19.67**	38.25**	1.48	2.29	.82	1.55	8.39**	16.16**	2.03
df	(1,134)	(1,138)	(1,149)	(1,149)	(1,149)	(1,212)	(1,218)	(1,218)	(1,217)
Step 2									
2. SAT Math	.31**	.29**	.04	.08	.00	.02	.14*	.22**	.03
3. Non-ability composite	.20**	.28**	.35**	.27**	.45**	.23**	.18**	.15*	.19**
R^2_{change}	**.04**	**.05**	**.12**	**.07**	**.19**	**.05**	**.03**	**.02**	**.02**
F_{change}	6.02**	7.54**	20.57**	11.35**	35.95**	11.23**	6.68**	4.64*	4.19*
df	(1,133)	(1,137)	(1,148)	(1,148)	(1,148)	(1,211)	(1,217)	(1,217)	(1,216)

Note. Values in table are Beta weights, unless otherwise indicated. Percent of incremental variance is shown in bold type. STEM: Science, Technology, Engineering, and Mathematics; GPA: Grade Point Average, HS: High School, BS: Bachelor of Science degree; Grad: Graduate degree, Particip: Participation. High school STEM competition prticipation, high school STEM club participation, and college STEM activity participation have been coded as 0 = No, I haven't participated, 1 = Yes I participated. * $p < .05$; ** $p < .01$.

CHAPTER VII

DISCUSSION ON THE PERSONALITY CORRELATES OF THE SCIENCE/MATH TRAIT COMPLEX

7.1 General Discussion

The literature review yielded three factors that are associated with choosing to be in an engineering or biological/physical sciences-related field: toughmindedness, cognitively-oriented behavior, and achievement. A series of exploratory and confirmatory factor analyses of the personality scales from the International Personality Item Pool indicated that the selected scales formed four factors: toughmindedness, cognitively-oriented behavior, achievement, and control. I proposed these personality factors as correlates of the science/math trait complex and of the STEM groups.

When the associations between the four hypothesized factors and the Big Five personality factors were investigated, a notable correlation was observed for each hypothesized factor. The substantial correlation between conscientiousness and achievement indicated that they are assessing the same construct. Other associations were smaller, indicating that the hypothesized factors may be capturing somewhat different behaviors. These notable associations were between toughmindedness and neuroticism, between control and conscientiousness, and between cognitively-oriented behavior and openness to experience. The associations of openness to experience, conscientiousness, and neuroticism with the science/math trait complex variables were also examined to see whether or not their pattern and magnitude of associations differed from those of the hypothesized personality factors. The pattern of associations was similar, but the hypothesized personality factors had larger correlations than did their Big Five correlates.

Contrary to initial expectations, STEM versus non-STEM major group differences were observed for only one of the 18 personality scales. STEM majors had lower emotionality, an indicator of toughmindedness, with a moderate effect size. Toughmindedness, cognitively-oriented behavior, achievement, and control were investigated in relation to the science/math trait complex. Toughmindedness was the only personality factor associated with the science/math trait complex with a loading higher than .40. Control and achievement loaded together with the science/math trait complex variables, but their loadings were smaller and they did not show consistent associations with the marker variables. Contrary to expectations, cognitively-oriented behavior was not an associate of the science/math trait complex, but was rather an associate of the intellectual/cultural trait complex, with consistent associations with the verbal domain of interests and abilities.

In fact, the associations of toughmindedness, cognitively-oriented behavior, achievement, and control with vocational criteria imply that these personality factors play a role at different stages of STEM-related decisions or experiences. Below, each factor is discussed separately, followed by a discussion of the results pertaining to the exploration of trait complex factors in relation to vocational criteria.

7.2 Toughmindedness

Toughmindedness was the personality marker of the science/math trait complex, and had significant associations with math, science, and spatial self-concept, STEM interest complexity, and intentions to pursue a career in a STEM field. In fact, an earlier study that supports this conclusion revealed that toughmindedness was significantly related to math and science achievement in middle school (Barton, Dielman, & Cattell, 1972).

Toughmindedness refers to being unsentimental, matter-of-fact, objective, and unaffected by feelings when appraising information and making decisions (Cattell et al., 1970). In the social psychological domain, the concept has been associated with competitiveness over resources and social dominance-orientation, which is defined as a desire for power distance and for having hierarchical relations as opposed to equality (Duckitt, Wagner, du Plessis, & Birum, 2002). The measure used in the referenced study included adjectives such as hard-hearted, unaffectionate, and compassionate (reverse coded) which are mostly related to the emotionality construct of the present study. It appears that the higher a person scores on a toughmindedness scale (or lower on emotionality), the more the person is ready to perceive competitiveness and power as desirable qualities. The goals of competing for resources and gaining power may be expressed through being unaffected by feelings while making decisions and appraising information.

These associations can shed light on why toughmindedness was associated with intentions to pursue a STEM career. Individuals who are lower on emotionality and are inclined to be matter-of-fact would prefer topics that would be objective in nature, and which can be independent of emotional judgment. Such individuals may interpret the objectivity of mathematics as desirable and may be more inclined to deal with mathematics. The present study results have indicated that toughmindedness and math abilities share a small correlation. From a trait complexes perspective, having higher toughmindedness, coupled with having higher math abilities, is associated with taking math courses in high school, choosing a STEM major, being successful in the chosen STEM major (as indicated with STEM-GPA), and intending to pursue a career in a STEM field. These associations may be explained by the competitive and social dominance orientation of toughminded people. STEM areas are publicly and academically viewed as prestigious occupations and it is known that they offer opportunities for earning income which would be more than that earned in lower complexity realistic and investigative occupations (O*NET, 2010). These arguments are in line with the literature review, which points out that engineers score lower on abasement and affiliation, and higher on dominance and self-sufficiency (Harris, 1994; Izard, 1960).

7.3 Achievement and Control

Achievement anf control were also associated with the science/math trait complex, but they had smaller loadings than did toughmindedness. Achievement had a small significant association with intentions to persist in STEM fields (pursuing a BS, graduate degree, and career) and control had a small association with pursuing a BS degree and with the number of math courses taken in high school. Neither achievement nor control were associated with choosing a STEM track. The most notable finding regarding the achievement and control factors was their associations with the college achievement indices. They were the only hypothesized personality factors to correlate with CGPA and STEM-GPA with moderate effect sizes. This finding is in accord with the literature where there is ample evidence indicating that the broad conscientiousness factor is associated with performance (e.g. Barrick & Mount, 1991). However, unlike achievement and control, the broader factor of conscientiousness was only slightly correlated with CGPA and not correlated with STEM-GPA.

It should be noted that achievement and control are perhaps not limited to performing in STEM areas. Though the present study did not include performance indices from non-STEM domains, based on the extant literature findings it is safe to suggest that achievement and control would be related to academic achievement in any domain. What the present study results support is that they also play a significant role in STEM fields by contributing to the science/math trait complex and its associates.

7.4 Cognitively-oriented Behavior

The literature review indicated that variables such as the Big Five openness to ideas facet, MBTI thinking (as opposed to feeling), Cattell's reasoning, and Hogan's creativity were associated with the engineering and scientist groups based on group mean differences between STEM and non-STEM majors. The reasons why the corresponding IPIP scales of the present study did not yield mean differences between STEM and non-STEM majors could be due to one or several of the following factors. The current college sample used for analyses was a highly selected one. Students may have been self-selected in applying to a college known to be competitive and cognitively challenging, which would result in a STEM and also non-STEM population looking for cognitively challenging pursuits. Such restriction of range in the present study sample may have attenuated a difference between majors that may exist in the wider college population.

Secondly, the effect sizes of the personality variables related to cognitively-oriented behavior reported in the literature are inconsistent in that they range from small to large. Samples used for comparing STEM groups to non-STEM groups are discrepant from each other in terms of size, and some samples are very small. Such sample characteristics may have yielded study-specific results, which are hard to generalize.

Moreover, the present study revealed that the construct of cognitively-oriented behavior is moderately correlated with the construct of openness to experience. It also conceptually resembles Ackerman’s (Goff & Ackerman, 1992) construct of Typical Intellectual Engagement (TIE). The main conceptual similarity between the two constructs is a preference for engaging in cognitive tasks, such as thinking, reasoning, analyzing, creating, reading, and problem solving. Neither of these factors specify a preference only for scientific and mathematically bounded cognitive challenges. Since the scale items are not contextually framed, participants are perhaps responding by taking their average behavior across domains that could be related to physical sciences, social sciences, humanities, or business ventures. Prior studies (e.g., Ackerman et al., 2001; Ackerman & Rolfhus, 1999) looking at trait complex structures found that TIE was a variable loading on the intellectual/cultural trait complex, which is consistent with the present study finding that cognitively-oriented behavior loaded on the intellectual/cultural trait complex factor.

In the present college sample, cognitively-oriented behavior seems to be related to more challenging vocational pursuits. Cognitively-oriented behavior was significantly associated with intentions to pursue a STEM graduate degree and career, and with a history of STEM-related competition/club participation. This factor, although not associated with choosing a STEM-related vocational track in the first place, was associated with attempting more challenging cognitive pursuits amongst STEM majors. A graduate level education entails more cognitively demanding pursuits such as reasoning about theoretical ideas, idea generation, complex problem solving, and reading more complex material. It is reasonable to suggest that students who have higher cognitive orientation would be more willing to go on for a graduate level education, whether or not they are in a STEM-related major.

7.5 Trait Complex Factors and their Associations with Vocational Criteria

The present study results yielded support for the personality factor of toughmindedness and also for STEM interest complexity as additional non-ability correlates of the science/math trait complex. Achievement and control also loaded on this factor, though with smaller loadings. The science/math trait complex composite was correlated with the STEM-related vocational criteria and had significant, mostly moderate associations.

The trait complex factor associations with vocational criteria support the view of utilizing the separate domains of individual differences (e.g., cognitive abilities, vocational interests, and personality variables) together in relation to valued outcomes. Recently, Kanfer, Wolf, Kantrowitz, and Ackerman (2010) have provided support for taking a whole-person approach to predicting academic performance by integrating variables related to cognitive abilities, knowledge, personality, vocational interests, self-concept, motivation, and decision-making styles as predictors. Specifically, their results indicated that a regression model that included non-ability traits related to learning orientation and self-management added 3% of significant incremental variance over abilities and knowledge in the prediction of GPA. These non-ability trait complexes included variables from the domains of motivation, personality, self-evaluations, and decision-making styles. In the present study, the ability trait with a moderate loading on the science/math trait complex factor was math abilities. Hierarchical regression analyses indicated that the non-ability variables of the science/math trait complex added significant incremental variance over math abilities in the prediction of STEM-GPA, STEM membership, intentions to further pursue a STEM field, and experiential variables indicating an attachment to STEM fields. This result provides further support for the role of non-ability measures in relation to academic criteria, and for the argument that separate dispositional constructs (i.e. abilities, interests, self-concept, and personality) need to be considered together in relation to valued criteria, as Ackerman (1996) suggests.

7.6 Conclusions

Toughmindedness, cognitively-oriented behavior, achievement, and control have an important role for STEM majors at different stages of the vocational track. Toughmindedness was the personality correlate of the science/math trait complex, and was associated with intending to pursue a STEM career. Once in a STEM major, achievement and control were the traits related to academic success as indicated by CGPA and STEM-GPA. The associations between cognitively-oriented behavior and criteria were observed for more cognitively-challenging pursuits, such as participating in STEM competitions and planning for a graduate education. Another notable finding of the study was that the Big Five personality factors had smaller associations with criteria than the hypothesized personality factors. It may be that toughmindedness, cognitively-oriented behavior, achievement, and control are capturing more specific behaviors related to STEM criteria.

Finally, the present study results provide support to Snow (1987), Ackerman (1997), and Lubinski (2000), who suggested going beyond domain-constrained explorations in investigating how dispositions relate to educational outcomes. In the present study, the trait complex of ability, personality, vocational interest, self-concept, and interest complexity variables, which were shown to be interrelated, had moderate associations with STEM-GPA, STEM major membership, and intentions to further pursue a STEM field, and had smaller associations with experiential variables indicating an attachment to STEM fields.

7.7 Limitations and Future Work

The present study was conducted with an undergraduate student sample from Georgia Tech, which is highly homogeneous in terms of cognitive abilities and certain personality traits such as cognitive-orientation and achievement-orientation. The magnitude of associations between the variables studied could be larger in the more general student population as compared to the present study sample. Further support is needed for the associations of the personality factors with the science/math trait complex and vocational criteria based on more heterogeneous samples. In addition to having more heterogeneous samples, larger samples are also needed to examine college major group differences. Future studies can utilize hierarchical regression modeling with a larger sample of adequately represented STEM majors.

Finally, the findings associated with the toughmindedness factor need to be replicated with different measures of the construct. The toughmindedness factor in this study included several IPIP scales which were theoretically representative of the broader toughmindedness factor: toughness (AB5C IV+V+), poise (CPI toughmindedness), emotionality (NEO openness to feelings), and self-sufficiency (6FPQ self-reliance). It should be noted that the definition of toughmindedness can somewhat vary based on what measure is used. For example, in the Eysenck Personality Inventory (EPQ; Eysenck & Eysenck, 1975) the toughmindedness factor is also known as the psychoticism factor, and it measures insensitivity, acting dangerously, and anti-social tendencies. The scales used in the present study do not include items related to anti-social behavior. Another scale by Duckitt (2001) assessing toughmindedness does not include items related to anti-social tendencies either, and limits the definition of toughmindedness to having low emotionality and compassion. The CPI masculinity scale (Gough, 1987) taps low emotionality, self-sufficiency, and being action-oriented without tapping into anti-social tendencies. The present study does not attempt to define toughmindedness as anti-social tendencies, but limits the definition to having low emotionality, and high self-sufficiency. Results need to be replicated using other scales with similar definitions of toughmindedness.

CHAPTER VIII

STUDY 2 HYPOTHESES AND METHOD

8.1 Study 2 Hypotheses

The newly developed STEM Interest Complexity scales were validated by investigating the construct and criterion-related validity.

8.1.1 Construct Validation

I studied the measure's construct validity by investigating its factor structure, and the associations with the interest themes and theoretically related constructs.

8.1.1.1 Confirmatory Factor Analyses

Initial construct validation of the scales was carried out using Confirmatory Factor Analysis (CFA) procedures. The first hypothesized model was tested with a CFA that is generally used for a multitrait-multimethod design. Four content factors (numerical, symbolic, spatial, and ideas) and three complexity factors (low, moderate, and high) were specified. Each observed variable (the 12 scales assessing low, moderate, and high complexity levels for each of the four contents) loaded on both the corresponding content and complexity factors.

Hypothesis 1a. The 12 scales loading onto both the corresponding content factors and the complexity factors will show adequate fit to the data.

The second hypothesized CFA model tests for a bifactor structure of STEM interest complexity, in which a global factor is hypothesized along with specific content factors. A bifactor model is preferable to a second-order CFA as it represents the content-specific factors as independent factors. It provides information as to whether or not a global factor can account for responses on all scales, and information on the role of content factors that are independent of the global factor. The strength of association between the content factors and the scales that load on them can be directly examined (Chen, West, & Sousa, 2006).

Hypothesis 1b. A bifactor structure, in which each complexity scale (low, moderate, and high scales for each domain) loads on the content factor it was designed to measure (numeric, symbolic, spatial, and ideas) and all complexity scales load on a global factor, will show adequate fit to the data.

8.1.1.2 Convergent and Discriminant Relations

Construct validity of the STEM Interest Complexity scales was also assessed through the scales' convergent and discriminant relations with the RIASEC interest themes. The STEM Interest Complexity Measure was developed as a vertical dimension for realistic and investigative themes, which means that those who show dominant realistic and investigative interests can rank high or low on complexity within that domain. This implies that theoretically no significant association between complexity level and interests should be expected. Nevertheless, investigative interests have small to moderate associations with various cognitive abilities and realistic interests have moderate associations with math and spatial abilities (e.g., Ackerman et al., 1995; Randahl, 1991). Since STEM interest complexity is also expected to correlate with abilities, moderate correlations between STEM Interest Complexity and investigative and realistic interests were expected.

Hypothesis 2. The STEM Interest Complexity scales assessing the four content domains and the general STEM interest complexity scale are expected to have moderate associations (between .20 and .40) with realistic and investigative interests, and small associations (.20 or smaller) with conventional, artistic, social, and enterprising interests.

8.1.1.3 Associations with Theoretically-related Constructs

I hypothesized that three other constructs will be associated with STEM Interest Complexity: cognitive abilities, typical intellectual engagement, and goal orientation.

8.1.1.3.1 Cognitive Abilities

Gottfredson's (1986) occupational aptitude map indicates that STEM occupations are the most complex cluster and have the highest required level of cognitive abilities. Moreover, Wilk, Desmarais, and Sackett (1995) showed that cognitive abilities were associated with moving towards occupations and jobs that are in line with an individual's level of cognitive ability. Based on these findings I proposed that cognitive abilities will be associated with STEM interest complexity. The literature on vocational interests and abilities indicates associations that range from .20 to .40 (e.g., Ackerman et al., 1995; Careless, 1999; Randahl, 1991). I expected slightly higher correlations with STEM Interest Complexity.

Hypothesis 3. Among STEM majors, math and spatial abilities will significantly correlate (between .30 and .50) with interest complexity in numeric, symbolic, spatial, and ideas domains. Verbal abilities are expected to significantly correlate (between .30 and .50) with ideas and general STEM interest complexity.

8.1.1.3.2. Intelligence as Personality: Typical Intellectual Engagement

Ackerman and Goff (1994) reported three facets of TIE: 1) Problem-directed thinking, which emphasized problem solving, complexity, and depth of learning, 2) Abstract thinking, which emphasized interest in thinking for its own sake, pleasure for deliberative thinking, and abstract, meditative, or philosophical thinking, and 3) Reading, which emphasized reading activities. The problem-directed thinking facet was associated with the Big Five conscientiousness factor and the ideas facet of the Big Five openness to experience factor, while the abstract thinking facet was associated with the ideas, values, and fantasy facets of the openness to experience factor (Ackerman & Goff, 1994; Ferguson, 1999) with moderate to strong correlations. TIE also has a moderate correlation with science-related interests.

Hypothesis 4. Among STEM majors, the TIE problem-directed thinking and the abstract thinking facets will significantly correlate with general STEM interest complexity. Problem-directed thinking will significantly correlate with the numeric, symbolic, and spatial scales. Abstract thinking will significantly correlate with ideas. I expect these correlations to range from .30 to .40.

8.1.1.3.3 Goal Orientation

Goal orientations, as identified by Dweck and Leggett (1988), were expected to relate to STEM interest complexity. Learning goal orientation is characterized by a belief in the controllability of intellectual abilities, exerting further effort in learning a task, finding hard tasks challenging, and persisting in times of failure, and is positively related to desired outcomes such as college GPA and negatively related to undesired outcomes such as behavioral disengagement (e.g., Button, Matthieu, & Zajac, 1996; Elliot &

Church, 1997; Grant & Dweck, 2003; Payne et al., 2007; VandeWalle, 1997). Performance-avoidance goal orientation is inversely related to a desire for mastery, hard work, intrinsic motivation, course grades, and long-term retention of material (Elliot & Church, 1997; Elliot & McGregor, 1999; VandeWalle, 1997). Learning orientation and performance-avoidance orientation were associated with non-ability variables with a range of medium effect sizes ($\hat{\rho}$ range = .25 to .48).

Hypothesis 5. Among STEM majors, learning goal orientation will be positively, and performance-avoidance goal orientation will be inversely, correlated with the general STEM interest complexity scale, and with the numerical, symbolic, spatial, and ideas scales, with magnitude of correlations ranging from .30 to .50.

8.1.1.3.4 Shared Variance with Related Constructs

Hypothesis 6: I hypothesize that cognitive abilities, TIE, and learning goal orientations will altogether have a medium association (f^2 = .13) with the STEM Interest Complexity scales. Five multiple regression analyses were conducted by regressing five factors—general STEM interest complexity, numeric interests, symbolic interests, spatial interests, and interest in ideas—on the predictors of cognitive abilities, a composite of the TIE problem-directed thinking and abstract thinking facets, and learning goal orientations. Population R^2 values of .13 and .26 have been suggested as medium and large effect size estimates, respectively (Cohen, Cohen, West, & Aiken, 2003). A power analysis indicated that a sample of 114 individuals provides adequate power (.90) to detect a medium effect size of f^2 = .13, with three predictors.

8.1.2 Criterion-Related Validation

Based on the accumulated evidence on interest/vocation fit, I expected that STEM Interest Complexity would be related to the choice of college major, attachment to STEM fields, intentions to persist in and further pursue a STEM field, intentions to pursue a complex occupation under Holland's realistic and investigative environments, satisfaction in STEM majors, and academic achievement in STEM-related course work.

8.1.2.1 Choice of Vocational Track

There are two dimensions to vocational choice: the direction of interest, as put forth by Holland's hexagonal model (1985, 1997), and the level of interest related to one's preferences to engage in complex and cognitively demanding work. The utility of the STEM Interest Complexity scales in the prediction of vocational choice needs to be demonstrated by: (1) discriminating between different vocational environments as indicated by the RIASEC themes (*direction* of interests), and (2) discriminating between job complexity levels within a vocational environment (*level* of interests). The present study was conducted based on a college student sample. Therefore, the criterion-related validity was studied by discriminating college majors that fall under the realistic and investigative themes from the other themes, and predicting intentions to pursue a complex occupation under the realistic and investigative themes.

STEM Interest Complexity scales were validated first by predicting college enrollment in STEM and non-STEM majors. Holland's interest themes, as assessed with the UNIACT on college student samples, have a 64% to 70% correct classification of college major membership based on hit rates (Prediger & Brandt, 1991; Swaney, 1995).

Hypothesis 7a. I hypothesize that STEM major membership of college students (i.e., the group of students enrolled in engineering, physical and biological sciences, mathematics) and non-STEM major membership (i.e., the group of students enrolled in liberal arts, management, humanities, social sciences, and architecture) will be predicted from the numeric, symbolic, spatial, ideas, and general STEM interest complexity scales, based on Discriminant Function Analyses (DFA). Two DFAs are conducted; one with the four contents as the predictors and one with the general STEM interest complexity scale as the predictor. For both analyses, I expect a correct classification percentage of more than 70% and a moderate strength of association between group membership and the predictors (between 13% and 20% of variance as indicated by the squared canonical correlation, corresponding to $f^2 = .15$ and $f^2 = .25$, respectively).

Hypothesis 7b. STEM Interest Complexity is hypothesized to show significant incremental variance over traditional interest assessments in the prediction of major membership. The dependant variable was dichotomously-coded major membership: being in STEM or non-STEM majors. Realistic and investigative interests were entered in the first step, math and science self-concept were entered in the second step, and the complexity scales were entered in the third step. I expect at least 5% to 10% incremental variance over traditional assessments in the prediction of group membership.

The following hypothesis was formed to show that the new measure assesses the level of interests within a vocational environment:

Hypothesis 8. STEM Interest Complexity scales will moderately (around $r = .30$) correlate with intentions of choosing a complex occupation.

8.1.2.2 Associations with Vocational Criteria

Criterion-related validity of the STEM Interest Complexity scales was further studied by investigating concurrent associations with vocational criteria. The aim of using traditional assessments of the direction of interests or self-efficacy is to predict satisfaction, persistence, and performance. Similarly, the aim of assessing the level of interest is to predict such outcomes. The literature indicates significant associations between interest-occupation fit and academic or job performance, persistence, and satisfaction, mostly with small effect sizes (e.g., Bruch & Krieshok, 1981; Kristof-Brown et al., 2005; Lindley & Borgen, 2002; Schaefers et al., 1997; Southworth & Morningstar, 1970; Spokane et al., 2000; Tracey & Robbins, 2006). Thus the following hypotheses were formed.

Hypothesis 9a. Among STEM majors, STEM Interest Complexity will correlate moderately (between .25 and .40) with intentions to persist in and further pursue STEM fields (e.g., a STEM BS degree, a STEM graduate education, a career in STEM).

Hypothesis 9b. Among STEM majors, STEM Interest Complexity will correlate moderately (between .25 and .40) with variables indicating an attachment to STEM, such as the number of math/science courses taken in high school, high school and college STEM-related competition and club participation, and the age at which one decided to pursue STEM.

Hypothesis 10. Among STEM majors, STEM Interest Complexity will correlate moderately (between .25 and .40) with major satisfaction and academic adjustment.

Hypothesis 11. Among STEM majors, STEM Interest Complexity will correlate moderately (between .25 and .40) with STEM-related GPA.

8.1.2.2.1 Relative Importance of Vocational Measures

Hypothesis 12. STEM Interest Complexity scales will contribute more to the prediction of vocational outcomes than the direction of interests or self-concept scales.

I performed a series of Dominance Analyses (Azen & Budescu, 2003) to determine the relative importance of STEM interest complexity, direction of interests, and self-concept. Specifically, I investigated the relative importance of a composite of STEM Interest Complexity scales, a composite of realistic and investigative interests, and a composite of science and math self-concept in relation to the following criteria: STEM-GPA; intentions to pursue a BS, graduate degree, and a career in STEM; major satisfaction; academic adjustment; and intentions to pursue a complex STEM occupation.

A series of regression analyses was run for each criterion, with subsets of predictors. With three predictors seven ($2^3 - 1 = 7$) squared multiple correlations were computed. To rank the predictors in terms of their relative importance, the predictive ability of one variable (i.e., R^2 associated with the predictor) needs to exceed that of another in all subset regressions (Budescu, 1993). I calculated each predictor's average contribution for each class of models with k = 0, 1, and 2 predictors and then averaged this contribution across all models to arrive at the relative importance of each predictor. For a variable X1, the equations for the three models to be averaged were as follows (Budescu, 1993, p. 546), where $C^{(k)}$ is the mean usefulness of x_1 across all models:

$Cx_1^{(0)} = \rho\, y.x_1^{\,2}$,

$Cx_1^{(1)} = [(\rho\, y.x_1x_2^{\,2} - \rho\, y.x_2^{\,2}) + (\rho\, y.x_1x_3^{\,2} - \rho\, y.x_3^{\,2})] / 2$,

$Cx_1^{(2)} = (\rho\, y.x_1x_2x_3^{\,2} - \rho\, y.x_2x_3^{\,2})$, and

$Cx_1 = (Cx_1^{(0)} + Cx_1^{(1)} + Cx_1^{(2)}) / 3$

8.2 Study 2 Method

8.2.1 Sample and Procedure

Hypotheses 3, 4, 5, 6, 8, 9, 10, 11, and 12 were tested based on a sample of students from STEM majors. The smallest correlation expected in these hypotheses was around .20. To detect a correlation as small as .20 a sample of 150 individuals was required for a power of .80. For the regression analyses, power analysis indicated that a sample of 141 would provide adequate power (.90) to detect a moderate effect size (f^2 = .13) with up to six predictors. To test hypothesis 2, a sample of 207 individuals, which would include students from STEM and non-STEM majors, was required to detect an effect size of .20 with a power of .90. Based on these power analyses, a sample of at least 150 individuals from STEM majors was required. For discriminant analysis purposes, 20 subjects per variable were needed for reliable results (Stevens, 2002), which required a total of 100 individuals for five variables. Based on the power analyses, a sample of at least 150 Georgia Tech undergraduate students from STEM majors and a sample of at least 60 individuals from non-STEM majors were needed.

A total of 446 participants enrolled in the online survey part of Study 2. Of these, 412 completed the survey entirely (92.3% response rate) and 34 completed partially, responding to between 10% and 90% of the survey. Those who had a 90% response rate were also retained for analyses. Of the participants who responded to the survey, 256 also participated in the in-class cognitive ability testing session (62.1% response rate). Of those who participated in the in-class testing, 244 granted permission to access their transcripts (93% response rate). Survey data were checked for random responding. If a participant took less than half the required time to complete the survey, as indicated by the report provided by SurveyMonkey, the case was deleted. Some cases were identified as having responded using the same scale value across all non-reverse and also reverse scored items in a scale or across scales. Such cases were also deleted. As a result 398 survey responses were retained, 240 cognitive ability test responses were retained, and 224 transcripts were retained for analyses.

Participant age ranged from 18 to 25, and the gender ratio was 47.4% men and 52.6% women. The sample consisted of 23.9% freshmen, 30.4% juniors, 17.1% sophomores, 16.8% seniors, and 9.5% who were in the 5^{th} or 6^{th} year of their undergraduate education. In terms of college major breakdown, 274 (68.8%) participants were in a STEM major. Of these, 161 completed the cognitive ability tests and 151 provided transcripts. Of the remaining sample, 86 (21.6%) were in a non-STEM major, and 35 (8.8%) indicated that they had transferred from a STEM major to a non-STEM major. Of these two groups, 78 completed cognitive ability tests and 73 provided transcripts. Among the STEM major sample, 178 (68%) participants were enrolled in an engineering major, 53 (19.3%) were enrolled in biological and physical sciences, 37 (13.5%) were enrolled in computer sciences, and 5 (1.8%) were enrolled in mathematics.

Students were recruited from the General Psychology courses in exchange for extra credit. The questionnaire package was administered in two parts to participants. The non-ability tests (Part 1) were uploaded on the Internet and students responded to the survey online. Completion of Part 1 took from one hour to 90 minutes. Ability tests (Part 2) were administered in paper-and-pencil format in a classroom setting. Participants were assigned to study sessions according to their availability. Part 2 lasted for 90 minutes.

8.2.2 Measures

Descriptions of measures introduced in Study 2 are provided below. Internal consistency reliabilities obtained in the present study are presented in the results chapter.

8.2.2.1 Demographic Information

Participants were asked to provide their age, sex, college major, year in major, CGPA, and SAT scores. In addition, participants were asked to provide permission to obtain their transcripts for course enrollment and grade information.

8.2.2.2 STEM Interest Complexity Scales

All items in the numeric, symbolic, spatial, ideas, and general STEM interest complexity scales were also included in Study 2. Two items (one in the numeric scale, one in the ideas scale) were changed from being reverse coded to non-reverse coded. The numbers of items in the scales were 28, 30, 24, 30, and 15, respectively.

8.2.2.3 Traditional Interest Assessments

Interests were assessed with the 90-item UNIACT (Lamb & Prediger, 1981). Math, spatial, science, and verbal self-concept were assessed with the 30-item measure (Ackerman & Goff, 1994; Ackerman et al., 1995; Ackerman et al., 2001).

8.2.2.4 Cognitive Abilities

The same cognitive ability tests from the ETS Kit (Ekstrom, French, Harman, & Dermen, 1976) used in Study 1 were administered to assess math/numerical, spatial, and verbal abilities. In addition, SAT math and verbal scores were obtained.

8.2.2.5 Intelligence as Personality

Intellectual engagement as a personality trait was assessed based on the Typical Intellectual Engagement (TIE) scale. The short form (Goff & Ackerman, 1992) had 59-items rated on a 6-point scale ranging from "strongly disagree" to "strongly agree." Sample items include "I prefer my life to be filled with puzzles I must solve" and "I read a great deal." An internal consistency reliability of .92 was reported together with construct validity evidence (Goff & Ackerman, 1992).

8.2.2.6 Goal Orientation

Goal orientation was assessed using items from four different measures: Learning and Performance Orientation Scales (Button, Mathieu, & Zajac, 1996), Goal Orientation Scales (VandeWalle, 1997), the Achievement Goal Scale (Elliot & Church, 1997), and the Achievement Goal Inventory (Grant & Dweck, 2003). All of these measures have been reported to have adequate internal consistency reliabilities and construct and criterion-related validities. Participants completed all the items from the four scales, but redundant items were not included in the analyses. Participants responded to 17 items assessing learning goal orientation, 10 items assessing performance-avoidance goal orientation, and 17 items assessing performance-prove goals. All items were rated on a 6-point scale ranging from "strongly disagree" to "strongly agree."

8.2.2.7 Intentions to Persist in and Further Pursue STEM Fields

Persistence in a STEM-related field, assessed longitudinally, has been defined in various ways, such as continuation with math and science courses in high school and college (Hanson, 1996; Wood & Brown, 1997), staying in the major originally chosen until graduation (Hewitt & Seymour, 1997), matriculation into graduate degree work (Hilton & Lee, 1988; Hollenshead, Wenzel, Lazarus, & Nair, 1996), and deciding to seek a career in science-math related fields after graduation (Rayman & Brett, 1995; Sonnert, 1995). Wyer (2003) suggested combining these definitions and assessing intentions to persist in STEM by measuring three levels of commitment: 1) short-term commitment which refers to students' intentions to stay in their current majors, 2) mid-level commitment which refers to degree attainment intentions, and 3) long-term commitment which refers to students' senses of themselves as scientists or engineers in the long-term.

In Study 1, STEM majors were asked 12 questions designed to rate their level of intentions regarding the STEM field. This measure was pilot tested in Study 1 and a 4-factor solution was obtained. Three of these factors, including 10 of the items, were interpreted as: 1) intentions to pursue a STEM BS; 2) intentions to pursue a STEM graduate degree; and 3) intentions to pursue a STEM career. The factors had good internal consistency reliabilities, and significant small to moderate associations with STEM interest complexity, realistic interests, investigative interests, math and science self-concept, and STEM-GPA. The same 10 items were included in Study 2.

8.2.2.8 STEM Major Satisfaction and Academic Adjustment

Participants' level of satisfaction in their major (e.g., "I am generally satisfied with my academic life in my major") and with specific aspects of their major-related experience (e.g., coursework, intellectual stimulation, "I enjoy the level of intellectual simulation in my courses) were assessed with the 7-item Satisfaction with the Academic Domain scale of Lent et al. (2005). Lent et al. reported an internal consistency reliability of .86, and moderate-to-strong associations with engineering self-efficacy, coping efficacy with barriers, goal progress, and engineering outcome expectations.

Academic adjustment was assessed with the 29-item Academic Adjustment subscale of the College Adjustment Scale (Baker & Siryk, 1984). Students rated their adjustment to the work they are required to do (e.g., "I am enjoying my academic work"), how well they are keeping up with their work (e.g., "I have been keeping up-to-date on my academic work"), the effectiveness of their efforts (e.g., "I have had trouble concentrating when I try to study"), and their opinion of what their academic environment is offering them (e.g., "I am satisfied with my program of courses"). Internal consistency reliabilities above .84 were reported, together with small to moderate correlations with criteria such as freshman attrition, getting counseling, and grade point average (Baker & Siryk, 1984; Baker, McNeil, & Siryk, 1985). In the present study, items were rated on a 6-point scale, from "strongly disagree" to "strongly agree."

8.2.2.9 Vertical Career Intentions

This measure was developed for the present study. It lists various occupations that correspond to Gottfredson's (1986) P1 (researching, designing, and modifying physical systems), P2 (operating and testing physical systems), and P3 (crafting or inspecting complex objects and repairing, operating, or setting up equipment or vehicles) clusters of occupations under the physical relations work domain, which correspond to RI and IR Holland codes. Occupations that fall in these clusters were drawn from occupations listed in DOT and O*NET. These occupations were ranked according to the level of complexity of dealing with data. Jobs corresponding to the highest four levels of dealing with data were selected (0 = Synthesizing, 1 = Coordinating, 2 = Analyzing, 3 = Compiling).

Occupations that corresponded to the data complexity level of "3" were grouped together, to form Cluster 1. Cluster 2 was formed by grouping occupations that corresponded to the complexity levels of "1" and "2," as these occupations were found to be similar with regard to their work activities, skills, and abilities. This cluster included technicians and technologists. Occupations that corresponded to the complexity level of "0" were grouped together, forming Cluster 3. This cluster included STEM occupations.

Each cluster was presented to the participants with a list of occupational titles and a brief description of the required work activities, skills, and abilities. Participants were asked to indicate whether or not they would like to work in one of the occupations in the cluster. They were instructed to make their decision assuming that occupations across clusters were equivalent in terms of pay and prestige. The participant got a score based on the highest level of cluster chosen. A score of 3 was assigned for choosing the highest-level cluster, 2 for choosing the mid-level cluster (without choosing the highest cluster), 1 for only choosing the lowest-level cluster, and 0 if the participant indicated that he or she did not wish to work in any of the clusters. This measure, including the clusters, their descriptions, and the list of occupations in each cluster, is presented in Appendix I.

Participants were also asked to rate how demanding the occupations in each cluster were, in terms of the level of cognitive effort required, on a 6-point scale ranging from "very undemanding" to "very demanding." The mean demand ratings for the three clusters were compared with *t*-test analyses to check for participants' perceptions of the cognitive demands of the three clusters.

CHAPTER IX

STUDY 2 RESULTS:

STEM INTEREST COMPLEXITY MEASURE VALIDATION

Descriptive statistics of the study variables are presented in the first section and results of hypotheses testing are presented in the second section of Chapter 9.

9.1 Descriptive Analyses

Study 1 results indicated that moderate- and high-complexity scales had sample means close to each other and had a similar pattern of associations with constructs and criteria. In Study 2, a unit-weighted z-score composites of the moderate- and high-complexity scales were formed to test the hypotheses. Items with inter-item correlations lower than .50 were dropped from further analyses. A total of seven items were dropped (two numerical high-complexity items, one numerical moderate-complexity item, two symbolic high-complexity items, one symbolic moderate-complexity item, and one spatial moderate-complexity item). Scale intercorrelations and internal consistency reliabilities are shown in Table 9.1. Descriptive statistics are presented in Table 9.2. Descriptive statistics for each complexity level are presented in Table J.4.

Table 9.1 STEM Interest Complexity Scale Intercorrelations

	Numeric	Symbolic	Spatial	Ideas	General STEM Interests
Numeric	(.93)				
Symbolic	.88**	(.97)			
Spatial	.65**	.72**	(.97)		
Ideas	.60**	.66**	.65**	(.95)	
General STEM Interests	.62**	.72**	.66**	.87**	(.96)

Notes. $N = 398$. Values in parantheses are internal consistency reliabilities. ** $p < .01$.

Independent sample t-test analyses were conducted to test for mean differences between the STEM and non-STEM participants and between the STEM participants and those who transferred from a STEM to a non-STEM major. Effect sizes of the differences were computed using Hedges' $\hat{g}$. Large group differences were observed between the STEM and non-STEM groups on all scales, with effect sizes ranging from .94 to 1.51. Medium to large differences were observed between the STEM and transfer groups, with effect sizes ranging from .61 to .96. Hedges' $\hat{g}$ coefficients are also reported in Table 9.2.

Table 9.2 Descriptive Statistics for the STEM Interest Complexity Domains

Scale (# of items)		Mean	Hedges' $\hat{g}$	Sd	Range	Skewness	α
Numeric (17)	STEM[1]	0.28		0.87	5.30	-0.63	0.92
	Non-STEM[2]	- 0.68	1.07[1,2]	0.98	4.26	0.24	0.92
	Transfer[3]	- 0.50	0.88[1,3]	1.04	3.97	-0.07	0.92
	All sample	0.00		1.00	5.30	-0.43	0.93
Symbolic (24)	STEM[1]	0.31		0.88	4.46	- 0.56	0.96
	Non-STEM[2]	- 0.82	1.30[1,2]	0.81	3.41	0.34	0.94
	Transfer[3]	- 0.39	0.77[1,3]	1.00	4.06	0.20	0.96
	All sample	0.00		1.00	4.46	- 0.27	0.97
Spatial (15)	STEM[1]	0.25		0.92	4.35	-0.42	0.94
	Non-STEM[2]	- 0.61	0.94[1,2]	0.92	3.91	0.32	0.93
	Transfer[3]	- 0.42	0.72[1,3]	1.00	3.72	-0.12	0.93
	All sample	0.00		1.00	4.35	-0.25	0.95
Ideas (26)	STEM[1]	0.34		0.74	4.06	-0.31	0.95
	Non-STEM[2]	- 0.97	1.51[1,2]	1.07	4.25	-0.10	0.97
	Transfer[3]	- 0.37	0.66[1,3]	1.10	3.86	0.07	0.97
	All sample	0.00		1.00	5.08	-0.66	0.97
General (12)	STEM[1]	0.31		0.80	4.44	-0.63	0.94
	Non-STEM[2]	- 0.80	1.31[1,2]	0.99	3.64	0.02	0.94
	Transfer[3]	- 0.37	0.61[1,3]	1.15	4.14	-0.23	0.97
	All sample	0		1.00	4.44	-0.60	0.95
STEM Interest Complexity*							
	STEM[1]	0.33		0.82	4.32	-0.57	0.86
	Non-STEM[2]	- 0.86	1.42[1,2]	0.92	3.98	0.02	0.87
	Transfer[3]	- 0.48	0.96[1,3]	1.03	3.92	-0.06	0.90
	All sample	0		1.00	4.56	-0.48	0.90

Notes. (*) Composite variable was re-standardized. (1,2) refers to the effect size of the mean difference between the STEM and non-STEM groups and (1,3) refers to the effect size of the mean difference between the STEM and transfer groups. Sample sizes are 274 for STEM, 86 for non-STEM, 35 for transfers, and 398 for the entire sample. Standard error of skewness for the samples are 0.15 for STEM, 0.26 for non-STEM, 0.40 for transfer, and 0.12 for the entire sample.

Descriptive statistics of the traditional interest assessments (i.e. direction of interests, self-concept) are presented in Table 9.3, those of the self-report variables used in the analyses of construct validation in Table 9.4, and those of the variables used for criterion validation in Table 9.5 and Table 9.6. Intercorrelations between variables used in construct validation are presented in Table 9.7 and vocational criteria used in criterion-related validation in Table 9.8.

College major mean differences were also computed for the relevant interest themes and self-concept scales. Small to medium mean differences were observed between STEM and non-STEM groups on realistic, investigative, and conventional interests, with effect sizes ranging from .29 to .57. Small differences on these variables were also observed between the STEM and transfer groups, with effect sizes ranging from .13 to .40. The STEM group showed higher interests on these scales, except for investigative interests where the transfer group had a higher mean.

STEM participants rated themselves as having higher math and science self-concept than did the non-STEM group. Differences were large, with effect sizes of .87 and 1.16 respectively. The STEM and transfer group differences were medium in size, .60 and .49 for math and science self-concept, respectively. A small mean difference between STEM and non-STEM majors was observed on the spatial self-concept scale, with an effect size of .38.

Scores on interest complexity, self-concept, SAT math, goal orientations, GPA, and STEM attachment variables were negatively skewed for the STEM sample.

Table 9.3 Descriptive Statistics for Traditional Interest Assessments

Scale (# of items)	Mean	Hedges' $\hat{g}$ Stem$^{(1)}$ *vs* Other$^{(2,3)}$	Sd	Range	Skewness	Cronbach's α
Interest Themes						
Realistic (15)						
STEM[1]	3.51		0.79	4.60	-0.27	0.88
Non-STEM[2]	3.18	0.42$^{(1, 2)}$	0.78	3.67	-0.36	0.86
Transfer[3]	3.41	0.13$^{(1, 3)}$	0.81	3.33	-0.22	0.90
All sample	3.44		0.80	4.60	-0.27	0.88
Investigative (15)						
STEM[1]	3.86		0.83	4.67	-0.13	0.90
Non-STEM[2]	3.32	0.57$^{(1, 2)}$	0.99	4.40	-0.30	0.92
Transfer[3]	4.05	-0.23$^{(1, 3)}$	0.82	3.67	-0.13	0.90
All sample	3.76		0.89	4.73	-0.31	0.91
Conventional (15)						
STEM[1]	3.14		0.90	4.53	0.08	0.93
Non-STEM[2]	2.87	0.29$^{(1, 2)}$	0.92	4.47	0.51	0.93
Transfer[3]	2.77	0.40$^{(1, 3)}$	1.05	4.08	0.22	0.94
All sample	3.05		0.93	4.80	0.16	0.93
Self-Concept						
Math (5)						
STEM[1]	4.94		0.78	4.40	-1.02	0.86
Non-STEM[2]	4.03	0.87$^{(1, 2)}$	1.11	4.80	0.26	0.90
Transfer[3]	4.34	0.60$^{(1, 3)}$	1.01	3.80	-0.40	0.89
All sample	4.68		0.96	5.00	-0.96	0.89
Science (6)						
STEM[1]	4.74		0.76	4.83	-0.76	0.88
Non-STEM[2]	3.59	1.16$^{(1, 2)}$	1.05	4.67	-0.19	0.90
Transfer[3]	4.28	0.49$^{(1, 3)}$	0.96	3.50	-0.18	0.87
All sample	4.44		0.98	5.00	-0.77	0.91
Spatial (13)						
STEM[1]	4.77		0.82	3.85	-0.73	0.92
Non-STEM[2]	4.44	0.38$^{(1, 2)}$	0.95	4.92	-0.95	0.92
Transfer[3]	4.79	-0.03$^{(1, 3)}$	0.76	2.62	-0.30	0.92
All sample	4.70		0.85	5.00	-0.81	0.92
Verbal (6)						
STEM[1]	4.75		0.95	4.33	-0.70	0.88
NonSTEM[2]	5.23	-0.50$^{(1, 2)}$	0.89	5.00	-2.01	0.89
Transfer[3]	5.20	-0.49$^{(1, 3)}$	0.75	2.50	-0.63	0.86
All sample	4.90		0.94	5.00	-0.93	0.88

Notes. All sample N = 398, STEM sample N = 274, non-STEM sample N = 86, transfer sample N = 35. (1,2) refers to the effect size of the mean difference between the STEM and non-STEM groups and (1,3) refers to the effect size of the mean difference between the STEM and transfer groups.

Table 9.4 Descriptive Statistics of Variables for Construct Validation

Scale (# of items)	Mean	Sd	Range	Skewness	Cronbach's α
ETS Kit Numeric*					
STEM (N = 161)	0.15	0.98	4.91	-0.05	
Non-STEM (N = 60)	- 0.38	0.95	3.95	0.00	
Transfer (N = 17)	0	1.02	4.28	0.17	
All sample (N = 240)	0	1.00	5.05	-0.01	
ETS Kit Spatial*					
STEM (N = 161)	0.11	1.03	4.67	-0.37	
Non-STEM (N = 60)	- 0.23	0.89	3.95	-0.05	
Transfer (N = 17)	- 0.22	0.98	3.10	0.62	
All sample (N = 240)	0	1.00	4.67	-0.19	
ETS Kit Verbal*					
STEM (N = 161)	0	1.03	5.75	-0.15	
Non-STEM (N = 60)	0	0.97	4.45	0.12	
Transfer (N = 17)	0.24	0.83	3.05	0.76	
All sample (N = 240)	0	1.00	5.75	-0.09	
SAT Math					
STEM (N = 210)	703	62.44	280	-0.32	
Non-STEM (N = 68)	659	56.49	230	-0.41	
Transfer (N = 12)	660	71.00	320	-0.45	
All sample (N = 303)	690	64.74	320	-0.29	
SAT Verbal					
STEM (N = 204)	645.5	70.79	320	0.02	
Non-STEM (N = 68)	661.8	71.00	320	-0.28	
Transfer (N = 12)	650	58.00	230	-0.11	
All sample (N = 297)	649	69.87	330	-0.05	
Learning goal orientation (17)					
STEM	4.61	0.64	3.82	-0.44	0.92
Non-STEM	4.51	0.69	4.59	-1.18	0.92
Transfer	4.52	0.73	3.59	-1.30	0.94
All sample	4.58	0.66	4.71	-0.72	0.92
Performance-avoid orient (6)					
STEM	4.11	0.76	4.20	-0.52	0.79
Non-STEM	4.15	0.73	3.30	-0.33	0.80
Transfer	4.22	0.73	3.30	0.16	0.82
All sample	4.12	0.75	4.40	-0.43	0.79
TIE Problem-solving (29)					
STEM	3.82	0.50	3.17	0.36	0.83
Non-STEM	3.79	0.58	3.07	0.16	0.86
Transfer	3.88	0.64	2.59	-0.10	0.88
All sample	3.82	0.53	3.31	0.24	0.84
TIE Abstract thinking (20)					
STEM	3.95	0.54	3.15	0.33	0.78
Non-STEM	3.99	0.67	2.90	0.19	0.85
Transfer	4.02	0.59	2.25	0.31	0.81
All sample	3.98	0.57	3.15	0.29	0.81

Notes. Variables with an asteriks (*) are formed using unit-weighted z-scores and the composite has been re-standardized. Alpha for cognitive ability tests could not be computed as data on individual items were not recorded. ETS: Educational Testing Service; TIE: Typical Intellectual Engagement.

Table 9.5 Descriptive Statistics of Variables for Critarion Validation

Scale (# of items)	Mean	Sd	Range	Skewness	α
CGPA (self-reported)					-
STEM (N = 259)	3.17	0.55	3.19	-0.71	
Non-STEM(N = 81)	3.19	0.56	2.42	-0.87	
Transfer (N = 32)	2.88	0.64	2.25	0.20	
All sample (N = 375)	3.15	0.56	3.19	-0.65	
STEM-course CGPA					-
STEM (N = 151)	3.07	0.61	2.50	-0.26	
Non-STEM (N = 56)	2.78	0.75	2.60	0.08	
Transfer (N = 17)	2.48	0.90	2.91	0.13	
All sample (N = 224)	2.95	0.69	3.00	-0.30	
# of high school math courses					-
STEM (N = 259)	4.60	0.95	7.00	1.56	
Non-STEM (N = 81)	4.34	0.77	4.00	1.57	
Transfer (N = 34)	4.20	0.59	3.00	1.80	
All sample (N = 377)	4.51	0.89	7.00	1.64	
# of high school science courses					-
STEM (N = 259)	4.97	1.45	8.00	1.29	
Non-STEM (N = 82)	4.30	1.13	7.00	1.05	
Transfer (N = 34)	4.76	1.35	6.00	1.32	
All sample (N = 378)	4.80	1.40	9.00	1.31	
Age decided to pursue STEM*	15.42	2.40	11.00	-0.62	-
Major Satisfaction* (7)	4.53	0.95	5.00	-0.74	0.92
Academic Adjustment* (24)	3.92	0.60	3.46	-0.08	0.86
Intentions to pursue STEM BS* (3)	5.24	0.93	5.00	-1.70	0.83
Intentions to pursue STEM grad degree* (3)	3.68	1.44	5.00	-0.24	0.84
Intentions to pursue STEM career* (4)	4.71	1.27	5.00	-1.01	0.91

Notes. (*) indicates descriptives are provided for the STEM sample. CGPA: Cumulative Grade Point Average; STEM: Science, Technology, Engineering, and Mathematics; BS: Bachelor of Science.

Table 9.6 Frequencies of the Categorical Vocational Criteria

	N	%
STEM membership		
Non-STEM	86	21.6
STEM	274	68.8
Transferred	35	8.8
High school STEM competition participation		
No	212	53.3
Yes	184	46.2
High cchool STEM club participation		
No	213	53.5
Yes	184	46.2
College STEM activity participation		
No	353	88.7
Yes	44	11.1

Notes. High school STEM competition participation, high school STEM club participation, and college STEM activity participation: 0 = No, I haven't participated, 1 = Yes I participated.

Table 9.7 Intercorrelations between Variables Used in Construct Validation

	1	2	3	4	5	6	7	8	9
1. ETS Kit Numeric	1.000								
2. ETS Kit Spatial	.454**	1.000							
3. ETS Kit Verbal	.176**	.074	1.000						
4. SAT Math	.522**	.444**	-.013	1.000					
5. SAT Verbal	.213**	-.003	.529**	.090	1.000				
6. Learning goal orientation	-.005	.017	.021	.021	.091	1.000			
7. Performance-avoid orientation	-.187**	-.198*	-.127*	-.158*	-.048	-.035	1.000		
8. TIE Problem-solving	.063	.064	.200**	-.020	.180**	.616**	-.176**	1.000	
9. TIE Abstract thinking	.047	.091	.267**	-.046	.243**	.464**	-.188**	.779**	1.000

Notes. Sample sizes are $N = 240$ for the ETS Kit abilities and self-reports, $N = 303$ for SAT scores and self-reports, $N = 398$ for self-reports, and $N = 192$ for ETS Kit abilities and SAT scores. ETS: Educational Testing Service; TIE: Typical Intellectual Engagement. * $p < .05$; ** $p < .01$.

Table 9.8 Intercorrelations between Vocational Criteria

	1	2	3	4	5	6	7	8	9	10	11
1. GPA	1.000										
2. STEM GPA	.794**	1.000									
3. STEM BS Intent	.097	.055	1.000								
4. STEM Grad Degree Intent	.038	-.026	.442**	1.000							
5. STEM Career Intent	-.016	.025	.638**	.378**	1.000						
6. # of HS Math Courses	-.004	-.037	-.171**	-.047	-.064	1.000					
7. # of HS Science Cours	-.011	.086	.054	-.056	-.017	.159**	1.000				
8. HS STEM Competition	.015	.143*	.000	.002	.000	.097	.167**	1.000			
9. HS STEM Club Particip.	.047	.165*	.085	.049	.072	.176**	.204**	.513**	1.000		
10. College STEM Activity	-.037	.055	.040	.051	.034	.051	.142**	.155**	.202**	1.000	
11. Age first wanted STEM	.009	.017	-.076	-.084	-.125*	.034	-.079	.053	.077	-.036	1.000

Notes. Samples sizes range from 213 to 393. GPA: Grade Point Average; STEM: Science, Technology, Engineering, and Mathematics; BS : Bachelor of Science; Grad: Graduate; HS : High School. * $p < .05$; ** $p < .01$.

9.2 Hypotheses Testing

Hypotheses that were tested to validate the STEM Interest Complexity scales are presented in two sections: 1) Construct validation, and 2) Criterion-related validation.

9.2.1 Construct Validation

Construct validation of STEM Interest Complexity was studied by investigating the measure's factor structure, its associations with the relevant interest themes and self-concept measures, and its associations with cognitive abilities, TIE, and goal orientations.

9.2.1.1 Confirmatory Factor Analyses

Two series of Confirmatory Factor Analyses (CFA) were performed, one to model the hypothesized content and complexity factor structure, and the other to model the hypothesized bifactor structure of interest complexity.

9.2.1.1.1 Modeling the Content and Complexity Factors

Two models were tested. In Model 1, I hypothesized that four content factors (numeric, symbolic, spatial, and ideas) and three complexity level factors (low, moderate, and high) would account for the responses. This model allowed for correlations among content factors and among complexity factors, but not between content and complexity factors. Factor loadings were freely estimated and factor variances were constrained to equal 1. The content and complexity covariances were freely estimated. Model 1 showed a very good fit to the data ($\chi^2(33) = 96.332$, $p < .000$; $CFI = 0.99$; $RMSEA = 0.07$; *C.I.* 05, .08; $SRMR = .02$). Average off-diagonal standardized residual was .014. All residual values fell between -.1 and +.1. Loadings were significant, except for the symbolic moderate-complexity scale loading on the symbolic factor. Loadings on the complexity factors (low, moderate, and high) ranged from .43 to .99. Loadings on the content factors ranged from .35 to .80, except for the symbolic scale, where loadings were negative. For the numeric and symbolic scales, loadings on the complexity factors were larger than loadings on the respective content factors (see Figure 9.1).

A nested 4-factor model was tested in Model 2 in which complexity factors were not specified. The model fit the data well ($\chi^2(48) = 221.057$, $p < .000$; *CFI* = 0.97; *RMSEA* = 0.10; *C.I.* 083, .108; *SRMR* = .03). The average off-diagonal standardized residual was .024 and most residual values (98.72%) fell between -.1 and +.1. All loadings were significant, and standardized loadings ranged from .66 to 1.00 (see Figure 9.2). A chi-square difference test indicated that Model 1 fit the data significantly better than did Model 2 ($\chi^2(15) = 124.725$, $p < .001$). The addition of complexity factors improved model fit. Thus, Hypothesis 1a was supported.

9.2.1.1.2 Modeling the Bifactor Structure

A bifactor structure of STEM Interest Complexity was tested, in which a global factor of STEM Interest Complexity was hypothesized along with specific content factors (numeric, symbolic, spatial, and ideas). The hypothesized bifactor model was defined as the following: (a) each complexity scale (low, moderate, and high) had a non-zero loading on the content factor it was designed to measure (numeric, symbolic, spatial, and ideas), and zero loadings on the other factors; (b) all scales had non-zero loadings on the global factor; (c) all five factors were uncorrelated with each other; and (d) error terms associated with each item were uncorrelated. Each factor variance was set to equal 1 and all the factor loadings were freely estimated.

The bifactor model showed good fit to the data ($\chi^2(42) = 191.874$, $p < .000$; *CFI* = 0.97; *RMSEA* = 0.09; *C.I.* .081, .108, *SRMS* = .043), supporting Hypothesis 1b. The unstandardized and the standardized factor loadings are presented in Table 9.9 and Figure 9.3. Results showed that all scales had significant loadings on the global factor. Symbolic low- and high-complexity scales had non-significant factor loadings on the specific symbolic interest factor, suggesting that most of the variance related to symbolic interests was explained by the global STEM interest complexity factor. All other specific factor loadings were significant, indicating they add unique information over the global factor. Factor loadings for the global factor were higher than factor loadings for the numerical and symbolic interest domains and the moderate-complexity spatial interest loading. All other loadings were comparable. Low-complexity scales had the lowest loadings on the global factor. Moderate- and high-complexity scale loadings on the global factor were comparable to each other within their respective domains.

Table 9.9 Bifactor CFA of the STEM Interest Complexity Scales

Scales/Factors	General Factor	Numerical	Symbolic	Spatial	Ideas
Numeric Low	.698 (.727)	.439 (.457)			
Numeric Mod	.788 (.887)	.360 (.404)			
Numeric High	.887 (.874)	.252 (.246)			
Symbolic Low	.764 (.793)		.080 (.082)		
Symbolic Mod	.957 (.945)		.332 (.328)		
Symbolic High	1.029 (.942)		.084 (.078)		
Spatial Low	.368 (.481)			.372 (.486)	
Spatial Mod	.805 (.790)			.590 (.580)	
Spatial High	.777 (.665)			.729 (.625)	
Ideas Low	.573 (.553)				.623 (.601)
Ideas Mod	.660 (.680)				.680 (.702)
Ideas High	.678 (.685)				.684 (.692)

Notes. *N* = 398. Values in parentheses are standardized coefficients. Coefficients at and above .24 are significant at the .05 level. Low: Low-complexity, Mod: Moderate-complexity, High: High-complexity.

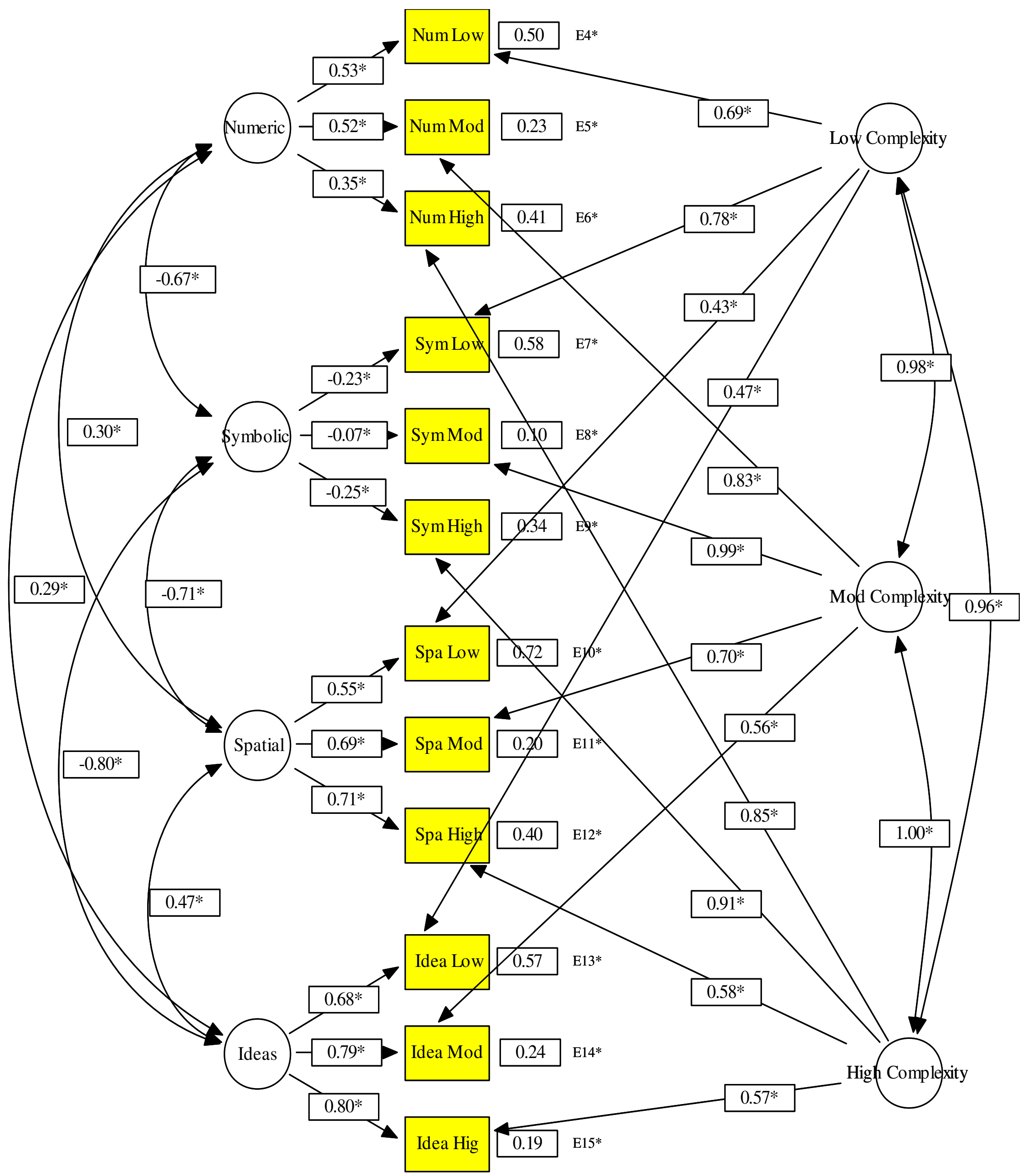

Figure 9.1 CFA Model 1: Modeling STEM Interest Content and Complexity Factors

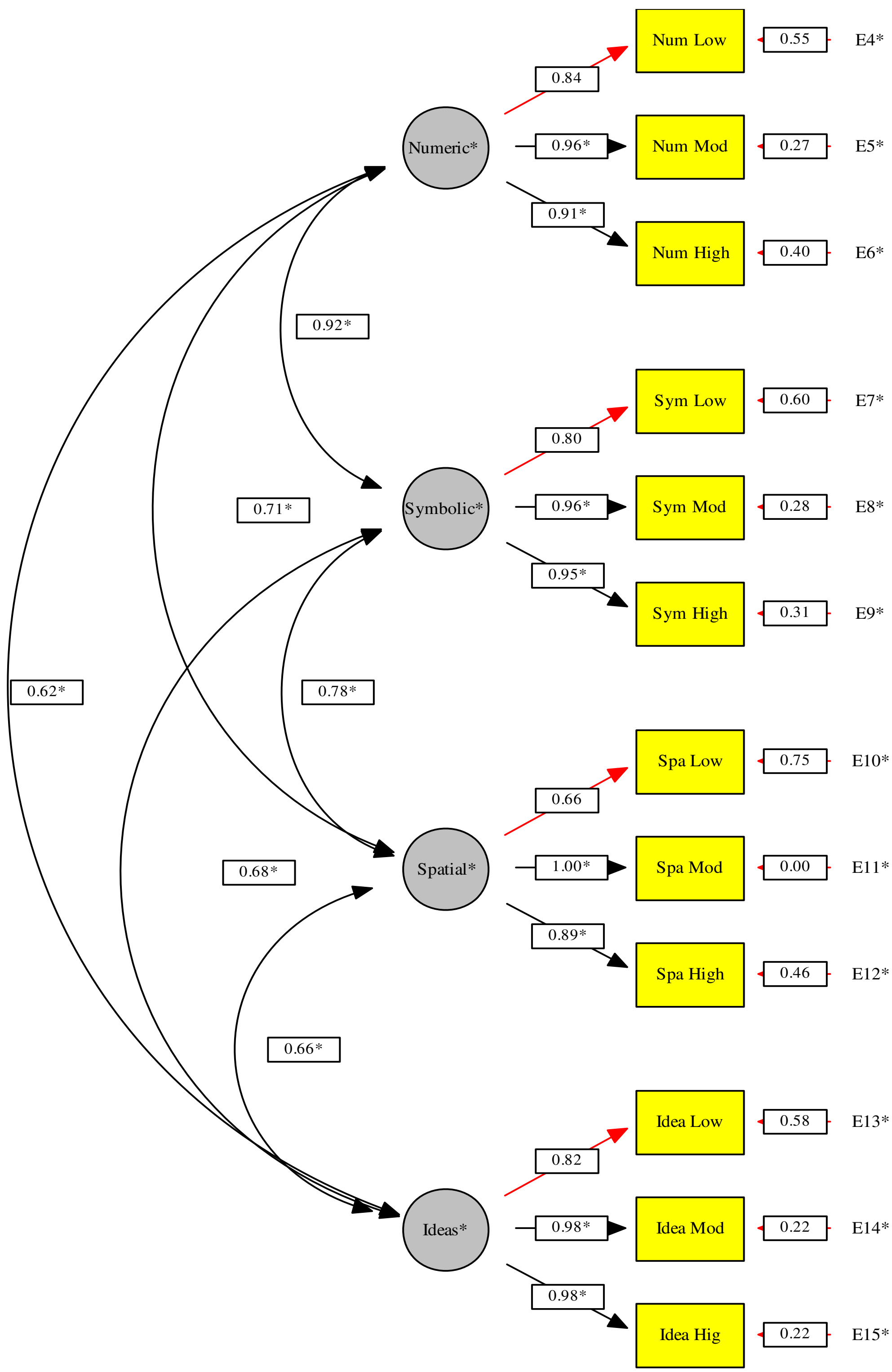

Figure 9.2 CFA Model 2: Modeling STEM Interest Content Factors

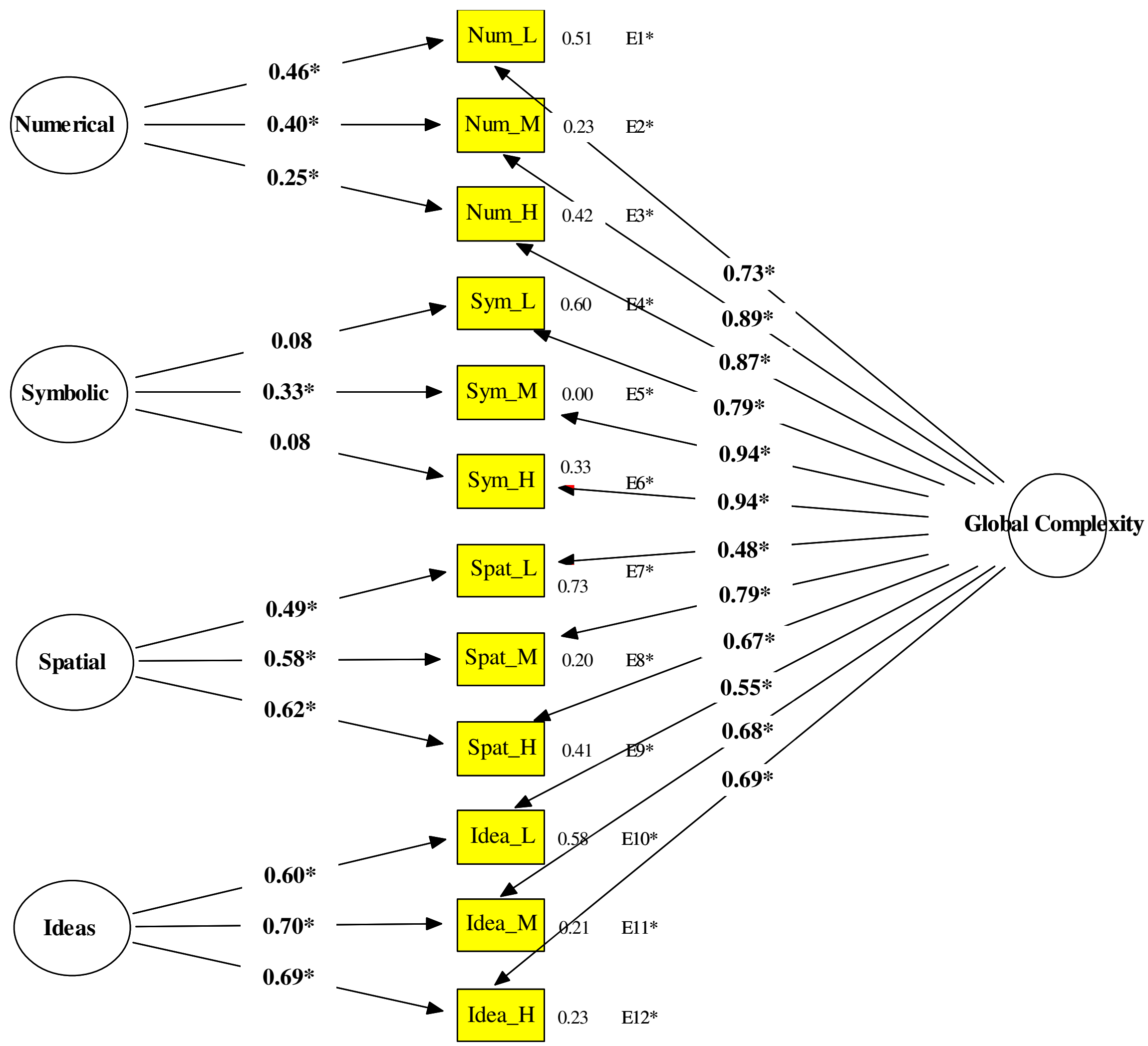

Figure 9.3 Bifactor CFA Model of STEM Interest Complexity

9.2.1.2 Convergent and Discriminant Relations with Traditional Interest Assessments

STEM Interest Complexity scales were expected to have moderate associations with the relevant interest themes (i.e. realistic, investigative) and negligible associations with the non-relevant themes (i.e. artistic, social, and enterprising). Interest complexity scales had small to moderate associations with realistic, investigative, and conventional interests, and had negligible associations with enterprising, artistic, and social interests. Hypothesis 2 was supported. Correlations are presented in Table 9.10.

Realistic interests had moderate associations (*r* range = .33 to .55) with all four interest complexity domains and general STEM interest complexity. The strongest association was with spatial interests (*r* = .55). Investigative interests had small associations with numeric, symbolic, and spatial interests (*r* range = .19 to .26), and moderate associations with ideas (*r* = .50) and general STEM interests (*r* = .49). Conventional interests had moderate associations with numeric (*r* = .50) and symbolic interests (*r* = .37) and smaller associations with other interests (*r* range = .14 to .19). Associations between interest complexity and artistic, social, and enterprising themes ranged from -.19 to .12.

Math and science self-concept had moderate to strong associations with all STEM Interest Complexity domains (*r* range = .41 to .68). Spatial self-concept moderately correlated with spatial interests (*r* = .42). Verbal self-concept had small negative correlations with numeric, symbolic, and spatial interests (*r* range = -.19 to -.24).

9.2.1.3 Associations with Theoretically-related Constructs

STEM Interest Complexity was expected to be moderately associated with cognitive abilities, goal orientations, and typical intellectual engagement. The following hypotheses were based on the STEM sample. Correlations are shown in Table 9.10, which also includes the non-STEM sample, transfer sample, and all sample correlations.

9.2.1.3.1 Hypothesis 3: Associations with Cognitive Abilities

I predicted that STEM Interest Complexity would have significant moderate associations with math and spatial abilities. In addition, ideas and general STEM interest complexity were expected to show moderate correlations with verbal abilities. According to the results, the STEM Interest Complexity scales had significant associations with cognitive abilities. In the entire sample, associations were moderate with math abilities (r range = .20 to .37), and were small to moderate with spatial abilities (r range = .14 to .34). However, associations were in the smaller-than-expected range for STEM majors. In the STEM sample, math abilities had significant small associations with numeric, symbolic, and spatial scales (r range = .15 to .29) and non-significant associations with ideas and general STEM interest complexity. Spatial abilities had a moderate association only with spatial interests (r = .24). Contrary to expectations, ideas and general STEM interest complexity did not significantly correlate with any of the ability domains in the STEM sample, except for the small correlation observed between SAT Math and general STEM interest complexity. Again, contrary to expectations, verbal abilities did not correlate with any interest complexity scale. Thus, Hypothesis 3 was partially supported.

9.2.1.3.2 Hypothesis 4: Associations with TIE

I predicted that, within the STEM sample, STEM Interest Complexity would be moderately associated with the problem-directed thinking and abstract thinking subscales of the TIE construct. As expected, ideas and general STEM interest complexity had significant moderate correlations with both the problem-directed thinking and the abstract thinking scales (r range = .45 to .57). Numeric, symbolic, and spatial interests had significant moderate correlations with problem-directed thinking (r range = .25 to .30) and small to moderate correlations with abstract thinking (r range = .20 to .28). The STEM Interest Complexity composite correlated .40 with problem-directed thinking and .36 with abstract thinking. Hypothesis 4 was supported. Correlations for the STEM sample, non-STEM sample, and the entire sample are presented in Table 9.10.

Table 9.10 Construct Validation: Associations between STEM Interest Complexity and Related Constructs

	Numeric	Symbol	Spatial	Ideas	General	Interest Complexity Composite
Interest Themes, *N* = 398						
Realistic	.33**	.34**	.55**	.37**	.33**	.45**
Investigative	.19**	.25**	.26**	.50**	.49**	.34**
Artistic	-.19**	-.15**	.03	-.06	-.08	-.11*
Social	-.07	-.10*	-.04	-.01	-.02	-.06
Enterprising	.12*	.05	-.02	-.05	-.03	.03
Conventional	.50**	.37**	.19**	.14**	.15**	.34**
Self-Concept, *N* = 398						
Math	.64**	.61**	.38**	.43**	.44**	.59**
Science	.44**	.53**	.41**	.68**	.66**	.59**
Spatial	.21**	.24**	.42**	.27**	.21**	.32**
Verbal	-.22**	-.23**	-.24**	-.07	-.12*	-.22**
Cognitive Abilities						
SAT – Math						
STEM	.23**	.29**	.17*	.13	.14*	.25**
Non-STEM	.27*	.23*	.32**	.15	.14	.29**
All sample	.33**	.37**	.29**	.25**	.26**	.35**
ETS Kit Numerical						
STEM	.25**	.17*	.15	.12	.08	.20**
Non-STEM	.36**	.34**	.20	.08	.12	.28*
All sample	.35**	.29**	.23**	.23**	.20**	.31**
ETS Kit Spatial						
STEM	.04	.05	.24**	.11	.06	.13
Non-STEM	.07	.14	.41**	.16	.12	.25
All sample	.14**	.16*	.34**	.20**	.16*	.24**
ETS Kit Verbal						
STEM	-.09	.03	.01	.10	.12	.01
Non-STEM	-.13	.07	.18	.05	.10	.04
All sample	-.12	-.02	.00	.02	.03	-.04
SAT Verbal						
STEM	-.12	-.03	-.13	.05	.04	-.07
Non-STEM	-.02	.01	-.14	.15	.11	-.01
All sample	-.10	-.06	-.13*	.03	.02	-.07
SAT Math&Verbal						
STEM	.06	.17*	.02	.12	.11	.11
Non-STEM	.16	.17	.10	.23*	.19	.21
All sample	.16**	.21**	.11	.20**	.19**	.19**
Typical Intellectual Eng						
Problem-directed think						
STEM	.25**	.30**	.28**	.57**	.52**	.40**
Non-STEM	.20	.30**	.34**	.49**	.44**	.40**
All sample	.24**	.30**	.30**	.49**	.46**	.38**

Table 9.10 (continued).

	Numeric	Symbol	Spatial	Ideas	General	Interest Complexity Composite
Abstract thinking						
STEM	.20**	.25**	.28**	.52**	.45**	.36**
Non-STEM	-.02	.09	.15	.37**	.32**	.18
All sample	.12*	.18**	.22**	.38**	.34**	.26**
Goal Orientation						
Learning goal						
STEM	.27**	.31**	.25**	.51**	.51**	.39**
Non-STEM	.23*	.34**	.36**	.26*	.27**	.35**
All sample	.28**	.33**	.29**	.40**	.41**	.37**
Performance-avoid						
STEM	-.09	-.16**	-.16**	-.06	-.10	-.18**
Non-STEM	-.07	-.14	-.16	-.19	-.10	-.16
All sample	-.09	-.16**	-.17**	-.12*	-.12*	-.18**

Notes. Sample sizes for self-report measures: STEM $N = 274$, non-STEM $N = 86$, all sample $N = 398$. Sample sizes for cognitive ability tests: STEM sample ETS Kit $N = 161$, SAT $N = 204$, non-STEM sample ETS Kit $N = 60$, SAT $N = 68$, all sample ETS Kit $N = 240$, SAT $N = 294$. Transfer sample is not included in correlational analysis due to small size ($N = 35$). ETS: Educational Testing Service; STEM: Science, Technology, Engineering, and Mathematics. * $p < .05$; ** $p < .01$.

9.2.1.3.3 Hypothesis 5: Associations with Goal Orientations

I predicted significant moderate associations between STEM Interest Complexity and goal orientations within the STEM sample. A total of 44 items from various goal orientation scales in the literature were used to assess three goal orientation domains: Learning, performance-prove, and performance-avoidance. All 44 items were subjected to PAF with Varimax rotation on the entire sample of participants. Three factors were extracted. All learning goal orientation items loaded together. Some items assessing performance-prove and performance-avoidance orientations loaded together with the non-corresponding scale or had cross-loadings. Five such items were dropped. Four other items with loadings less than .40 were also dropped. Three factors were formed, which were interpreted as learning-goal, performance-prove, and performance-avoidance orientation. Internal consistency reliabilities were .92, .88, and .79, respectively. Only learning-goal and performance-avoidance orientations were hypothesized as interest complexity correlates. Learning-goal and performance-avoidance orientations had a close-to-zero correlation.

STEM sample associations with learning-goal orientation ranged from .25 to .51 (see Table 9.10). The strongest correlations were with ideas and general STEM interest complexity. As expected, performance-avoidance orientation was inversely related to interests, but with small effect sizes. Only the associations with symbolic and spatial interests were significant (*r* = -.16). Thus, Hypothesis 5 was partially supported.

9.2.1.3.4 Hypothesis 6: Shared Variance between Interest Complexity and Constructs

I predicted that the related constructs would altogether have a medium strength of association with the complexity scales. Squared multiple correlation values of .13 and .26 have been suggested as medium and large effect size estimates, respectively (Cohen et al., 2003). Five regression analyses were run where each interest complexity domain was entered as the dependent variable. Learning-goal orientation, a unit-weighted z-score composite of TIE problem-directed and abstract thinking scales, and SAT Math scores were entered as predictor variables. In the prediction of spatial interests, spatial ability scores, rather than SAT Math scores, were entered as the cognitive ability predictor.

Hypothesis 6 was first tested in the STEM major sample (*N* = 206). Support was found for the association between the predictors and STEM interest complexity scores with medium to large effect sizes (R^2 range = .14 to .38). The three predictor variables shared between 14% and 22% variance with numeric, symbolic, and spatial interests, 38% variance with ideas, and 35% variance with general STEM interest complexity. Hypothesis 6 was supported (see Table 9.11).

Table 9.11 Shared Variance between Interest Complexity Scales and Constructs

	Numeric	Symbolic	Spatial	Ideas	General
Cognitive abilities*					
STEM sample	.22**	.28**	.19**	.12*	.13*
All Sample	.32**	.37**	.32**	.26**	.26**
TIE problem directed and abstract thinking					
STEM sample	.11	.17*	.32**	.40**	.29**
All Sample	.09	.15*	.17*	.34**	.27**
Learning goals					
STEM sample	.22**	.18*	.13	.27**	.35**
All Sample	.22**	.21**	.25**	.18**	.24**
R^2					
STEM sample	.14	.18	.22	.38	.35
All Sample	.19	.24	.26	.28	.27
F					
STEM sample	10.92**	14.91**	15.06**	42.20**	37.21**
All Sample	23.27**	31.57**	27.28**	39.41**	37.55**
df					
STEM sample	3, 206	3, 206	3, 157	3, 206	3, 206
All Sample	3, 299	3, 299	3, 236	3, 299	3, 299

Notes. Values are Beta weights, unless otherwise indicated. (*) As an indicator of cognitive abilities SAT Math was entered to predict numeric, symbolic, ideas, and general interests, and ETS Kit spatial abilities was entered to predict spatial interests. TIE: Typical Intellectual Engagement; STEM: Science, Technology, Engineering, and Mathematics. * $p < .05$; ** $p < .01$.

9.2.2 Criterion-Related Validation

I hypothesized that STEM interest complexity would be moderately associated with STEM major membership; an attachment to STEM fields (as indicated by intentions to persist in and further pursue STEM fields, and several experiential variables related to engaging in STEM-related work in high school and college); college major satisfaction; academic adjustment; and achievement in STEM-related coursework.

9.2.2.1 Choice of Vocational Track

I hypothesized STEM interest complexity to be associated with the *direction* and *level* of vocational choice. Hypotheses 7a and 7b pertain to the associations with the direction of choice. Hypothesis 8 pertains to the association with the level of choice.

9.2.2.1.1 Hypothesis 7a: Associations with the Direction of Vocational Choice

I expected that students enrolled in the vocational environments based on the RIASEC themes (i.e. STEM versus non-STEM majors, which pertain to the realistic/investigative themes and the other themes, respectively) would be discriminated based on the interest complexity scales. A series of Discriminant Function Analyses (DFA) were performed (see Table 9.12). Two DFAs were conducted to test for Hypothesis 7a, where STEM ($N = 274$) versus non-STEM ($N = 86$) major membership was predicted. Students who transferred from a STEM to a non-STEM major were excluded from these two analyses.

The first DFA included the numeric, symbolic, spatial, and ideas scales. The second DFA only included the general STEM interest complexity scale. In both analyses the function significantly discriminated between major membership (Wilk's *lambda* = .67, $\chi^2(4) = 140.55$, $p < .01$, and Wilk's *lambda* = .76, $\chi^2(1) = 112.37$, $p < .01$, respectively). Squared canonical correlations were .33 and .24, respectively. According to the classification results using prior probabilities, 51.2% and 40.7% of non-STEM and 94.2% and 93.1% of STEM major members were classified correctly. Overall correct classifications were 85% and 80.6%. Hypothesis 7a was supported with moderate effect sizes and overall correct classification percentages above 70%, as expected. In the first analysis, ideas had the highest correlation with the discriminating function (.93), followed by symbolic (.80), numeric (.66), and finally spatial interests (.58).

To predict the membership of students who transferred from a STEM to a non-STEM major ($N = 35$) versus those who remained in a STEM major ($N = 274$), two additional DFAs were conducted with the same predictors. The students who had been in a non-STEM major since enrollment were not included in these analyses. Both functions significantly discriminated between major membership (Wilk's *lambda* = .90, $\chi^2(4)$ = 31.65, $p < .01$, and Wilk's *lambda* = .94, $\chi^2(1)$ = 20.20, $p < .01$, respectively). Squared canonical correlations were .10 and .06, respectively. According to classification results using prior probabilities, 14.3% and 8.6% of those who transferred 98.5% and 99.3% of STEM majors were classified correctly. Overall correct classification was 89% in both analyses. In the analysis with four predictors, ideas had the highest correlation with the function (.87), followed by numeric (.85), symbolic (.74), and spatial interests (.69).

Finally, one more DFA was run to discriminate between all three groups of majors (i.e. STEM, non-STEM, and transfers). Only the first function, on which all four interest complexity domains loaded, significantly discriminated between major membership (Wilk's *lambda* = .68, $\chi^2(4)$ = 148.77, $p < .01$). The squared canonical correlation was .31. Ideas had the highest correlation with the discriminating function (.92), followed by symbolic (.81), numerical (.69), and spatial interests (.61). Classification results indicated that 50% of non-STEM, 94.2% of STEM, and 0% of the transfer group were classified correctly. Overall correct classification percentage was 76.2%. Examination of the canonical discriminant function plot (see Figure 9.4) indicated that Function 1 separated between the non-STEM and the STEM groups. The transfer group centroid (group centroid = -0.459) was in between the non-STEM group centroid (group centroid = -1.162) and the STEM group centroid (group centroid = 0.423) along Function 1.

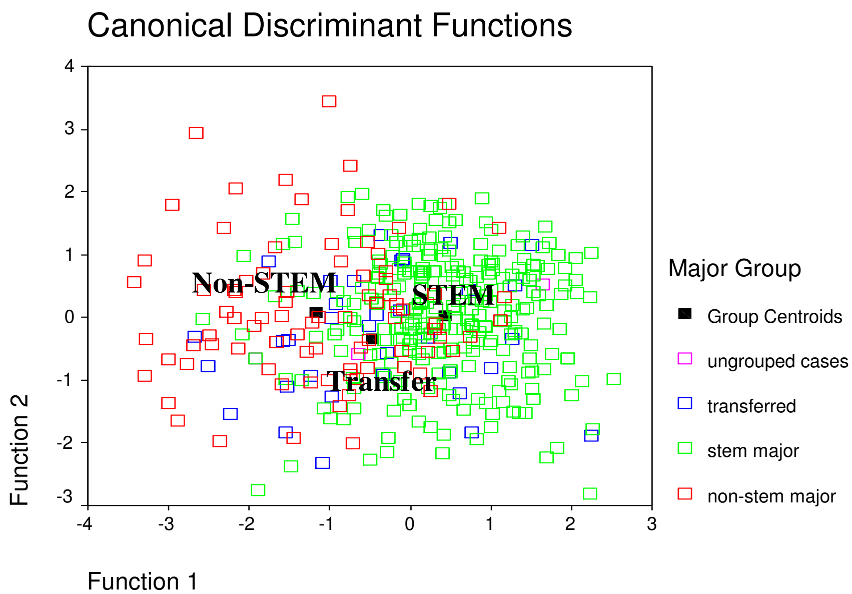

Figure 9.4 Interest Complexity Functions Discriminating between Majors

For comparison purposes, additional DFAs were performed with traditionally used interest assessments as the predictors. Specifically, realistic and investigative interests and math and science self-concept scores were entered as predictors. Functions discriminating the STEM and non-STEM groups, and the STEM and transfer groups, were both significant, with squared canonical correlations of .28 and .07, respectively. All DFA results are summarized in Table 9.12, where the list of predictors is shown together with the squared canonical correlation and classification results based on prior probabilities. The STEM Interest Complexity scales showed the largest squared canonical correlation. Overall correct classification percentages were very similar across the DFA models. However, the STEM Interest Complexity scales correctly classified a higher percentage of participants in the non-STEM and transfer groups.

Table 9.12 Major Membership Prediction based on Discriminant Function Analyses

	STEM vs Non-STEM Membership				STEM *vs* Transfer Membership			
	Effect size	Correct classification %			Effect Size	Correct classification %		
Predictors	R^2	STEM	Non-STEM	Overall	R^2	STEM	Trans-Fer	Overall
Model 1: Numeric Symbolic Spatial Ideas	.33	94.2%	51.2%	84%	.10	98.5%	14.3%	89%
Model 2: General Scale	.24	93.1%	40.7%	80.6%	.06	99.3%	8.6%	89%
Model3: Realistic Investigative Math-concept Science-concept	.28	94.9%	45.3%	83.1%	.07	99.3%	5.7%	88.7%

Notes. Effect size is indicated by the squared canonical correlation. Prior probabilities for the STEM and non-STEM classification are .761 and .239, respectively. Prior probabilities for the STEM and transfer group classification are .887 and .113, respectively.

9.2.2.1.2 Hypothesis 7b: Direction of Vocational Choice: Adding Incremental Variance

I hypothesized that STEM Interest Complexity would add significant incremental variance over traditional interest assessments in the prediction of major membership. Two hierarchical regression analyses were performed, in which dichotomized major group membership was regressed on realistic and investigative interests in the first step, and math and science self-concept in the second step. In the third step, the interest complexity composite was entered in the first analysis, and general STEM interest was entered in the second. All three steps of the two analyses were significant in the prediction of STEM versus non-STEM majors. The STEM Interest Complexity composite added 6% variance (*Multiple R* = .58, R^2_{change} = .06, $F_{change}(1,354)$ = 29.69, $p <$ .01, β = .35, t = 5.45, p < .01). General STEM interest complexity added 3% variance

(*Multiple R* = .56, R^2_{change} = .03, F_{change}(1,354) = 17.30, $p < .01$, β = .27, t = 4.16, $p < .01$). In the prediction of STEM versus transfer students, the second and third steps were significant. STEM Interest Complexity composite added 4% variance (*Multiple R* = .34, R^2_{change} = .04, F_{change}(1,303) = 13.72, $p < .01$, β = .27, t = 3.70, $p < .01$) and general STEM interest complexity added 4% variance (*Multiple R* = .33, R^2_{change} = .04, F_{change}(1,354) = 12.08, $p < .01$, β = .24, t = 3.48, $p < .01$). Thus, Hypothesis 7b was supported. Results of the hierarchical regression analyses are tabulated in Table 9.13.

Table 9.13 Hierarchical Regression Analyses in the Prediction of Major Membership

Dependant Variable	STEM *vs* Non-STEM	STEM *vs* Transferred
Step 1		
1. Realistic Interests	.09	.07
2. Investigative Interests	.23**	-.09
$\boldsymbol{R^2}$	**.08**	**.01**
F(df)	14.50** (2, 357)	1.47 (2, 306)
Step 2		
1. Realistic Interests	.06	.06
2. Investigative Interests	.04	-.14*
3. Math self-concept	.16**	.13
4. Science self-concept	.38**	.17*
$\boldsymbol{R^2_{change}}$	**.20**	**.06**
F_{change} *(df)*	49.54** (2, 355)	10.21** (2, 304)
Step 3		
1. Realistic Interests	-.05	-.04
2. Investigative Interests	.01	-.13*
3. Math self-concept	.03	.03
4. Science self-concept	.28**	.10
5. STEM Interest Complexity*	.35**	.27**
$\boldsymbol{R^2_{change}}$	**.06**	**.04**
F_{change}*(df)*	29.69** (1, 354)	13.72** (1, 303)
Alternative Step 3		
1. Realistic Interests	.02	.03
2. Investigative Interests	-.02	-.18**
3. Math self-concept	.13*	.10
4. Science self-concept	.26**	.07
5. General Complexity	.27**	.24**
$\boldsymbol{R^2_{change}}$	**.03**	**.04**
F_{change}*(df)*	17.30** (1, 354)	12.08** (1, 303)

Notes. Unless otherwise indicated, values in table are Beta coefficients. Percent of incremental variance is shown in bold type. * $p < .05$; ** $p < .01$.

9.2.2.1.3 Hypothesis 8: Associations with the Level of Vocational Choice

I hypothesized that participants with higher levels of STEM Interest Complexity would show intentions to choose a cluster of occupations with higher levels of complexity. Of the STEM participants who responded to the Vertical Career Intentions Form (see Appendix I), 71.3% wanted to work in a highly-complex occupation, 11.4% wanted to work in a moderately-complex occupation, 5.5% wanted to work in a low-complexity occupation, and 11.8% indicated they did not want to work in any of the clusters. Paired samples *t*-tests were conducted to check whether or not participants perceived the clusters to have different levels of cognitive demand. Participants perceived the high-complexity cluster as significantly more cognitively demanding than the moderate-complexity cluster ($M_{\text{high}} = 5.27$, $M_{\text{mod}} = 4.83$, $t(270) = 8.00$, $p < .01$), and perceived the moderate-complexity cluster as significantly more cognitively demanding than the low-complexity cluster ($M_{\text{mod}} = 4.83$, $M_{\text{low}} = 3.84$, $t(268) = 16.2$, $p < .01$).

Vertical occupational intentions correlated between .24 and .29 with the STEM interest complexity scales and .32 with the complexity composite. Traditional interest assessments and vertical occupational intentions had correlations ranging from .09 to .20. Hypothesis 8 was supported. Correlations are presented in Table 9.14.

Table 9.14 Correlations between Interest Assessments and Vertical Career Intentions

	STEM Interest Complexity Scales						Traditional Interest Assessments				
	N	Sy	Sp	Id	Gen	Com	R	I	Mat	Sci	Spa
Vertical Career Intentions	.25**	.28**	.29**	.29**	.29**	.32**	.19**	.09	.18**	.20**	.17**

Notes. N: numeric, Sy: symbolic, Sp: spatial, Id: ideas, G: general STEM scale, Com: numeric, symbolic, spatial, and ideas composite, R: realistic interests, I: investigative interests, Mat: math self-concept, Sci: science self-concept, Spa: spatial self-concept. * $p < .05$; ** $p < .01$.

9.2.2.2 Associations with Vocational Criteria

The criterion-related validity of the STEM Interest Complexity scales was studied concurrently by investigating the scales' associations with vocational criteria such as persistence, performance, and satisfaction in the academic arena.

9.2.2.2.1 Hypotheses 9a&b: Persisting in and Attachment to STEM Areas

Hypothesis 9a was formulated to assess the persistence criterion. As the data were gathered concurrently, STEM participants were asked to rate their intentions for attaining a STEM area degree and pursuing a STEM career in the long-term. After pilot testing the scale in Study 1, the 10 items yielding a 3-factor structure were included in Study 2. CFA of the 3-factor model fit the data well in Study 2 ($\chi^2(32) = 202.6$, $p < .01$ $CFI = .92$, $RMSEA = .14$). The three factors of intentions to pursue a STEM BS, a STEM graduate degree, and a STEM career had internal consistency reliabilities of .83, .84, and .91, respectively.

Intentions to pursue a STEM field were correlated with STEM interest complexity (see Table 9.15). Correlations were mostly moderate for intentions to pursue a STEM BS (*r* range = .21 to .39) and career (*r* range = 27 to .37), and were in the smaller range for pursuing a graduate degree (*r* range = .10 to .25). General STEM interests correlated with these factors .41, .42, and .32, respectively, and the STEM interest composite correlated .31, .39, and .19, respectively. Hypothesis 9a was supported.

Intentions to further pursue a STEM field are an indication of participants' attachment to these fields. Attachment to STEM fields was assessed with several experiential variables relating to participants' high school and college experiences.

STEM Interest Complexity scales had some small significant correlations with the experiential variables (*r* range = .14 to .21), but only within the entire sample. In general, correlations were non-significant or very small within the STEM sample. The only attachment variable that had significant correlations with STEM interest complexity was STEM activity participation at college (*r* range = .13 to .16). Hypothesis 9b received only partial support. Correlations with attachment variables are presented in Table 9.15.

9.2.2.2.2 Hypothesis 10: Associations with Major and Academic Satisfaction

Hypothesis 10 was tested only within the STEM sample. Moderate correlations between STEM major satisfaction and STEM Interest Complexity were observed (*r* range = .24 to .37). Correlations between adjustment to academic life and numeric, symbolic, ideas, and general STEM interests were also moderate (*r* range = .25 to .31). The STEM Interest Complexity composite correlated .35 with major satisfaction and .29 with academic adjustment (see Table 9.15). Hypothesis 10 was supported.

9.2.2.2.3 Hypothesis 11: Associations with Achievement: STEM GPA and Course Grades

I hypothesized that STEM Interest Complexity would moderately correlate with college achievement. Since these scales pertain to STEM tasks, they were correlated with STEM-GPA and specific course grades. STEM-GPA was calculated based on the stem quality points divided by the stem hours ([∑(stem course grade*stem hours)]/stem hours). Within the STEM major sample, all interest complexity scales significantly correlated with STEM GPA (*r* range = .21 to .27). STEM Interest Complexity composite correlated .32 in the STEM sample and .34 in the entire sample. Entire sample correlations were higher than the STEM sample ones, ranging from .21 to .34 (see Table 9.16).

Table 9.15 Concurrent Criterion-related Validation of the STEM Interest Complexity Scales: STEM Attachment and Satisfaction

Measures	# of High School Math Courses	# of High School Science Courses	H. S. STEM Compe-tition	H. S. STEM Club Attend	College STEM Competi-tion/Fair	Age decided to enter STEM	STEM BS Degree Intention	STEM Graduate Degree Intention	STEM Career Intention	Major Satisfa-ction	Acad. Satisfa-ction
Numeric											
Stem major	.05	.00	.09	.05	.06	-.06	.24**	.14*	.35**	.29**	.30**
All sample	.14**	.06	.17**	.15	.10*						
Symbolic											
Stem major	.06	-.02	.09	.10	.13*	-.09	.24**	.18*	.33**	.30**	.25**
All sample	.15**	.08	.18**	.19**	.15**						
Spatial											
Stem major	.11	.03	.06	.04	.16*	-.04	.21**	.10*	.27**	.24**	.13*
All sample	.17**	.14**	.18**	.11**	.15**						
Ideas											
Stem major	.01	.04	.07	.06	.14*	-.08	.39**	.25*	.37**	.37**	.31**
All sample	.09	.19**	.19**	.15**	.15**						
General											
Stem major	.01	.08	.11	.09	.14*	-.10	.41**	.32**	.42**	.37**	.31**
All sample	.10	.18*	.21**	.16**	.15**						
STEM Interest Complexity Composite											
Stem major	.07	.01	.09	.07	.15*	-.08	.31**	.19**	.39**	.35**	.29**
All sample	.16**	.13**	.20**	.17**	.16**						

Notes. Interest complexity domains are a composite of the respective moderate- and high-complexity scales. The STEM Interest Complexity is a composite of numeric, symbolic, spatial, and ideas scales. All composites are formed using unit-weighted z-scores. High School STEM Competition Participation, High School STEM Club Participation, and College STEM Competition/Fair Participation has been coded as 0 = No, I have not participates, 1 = Yes, I have participated. STEM: Science, Technology, Engineering, and Mathematics; H.S.: High School, BS: Bachelor of Science; Acad: Academic. **p* < .05; ***p* < .01.

Specific STEM courses with a relatively high rate of student enrollment (i.e. Calculus 1, and 2, Physics 1, and General Chemistry) were also correlated with the STEM Interest Complexity scales. Within the STEM sample, the interest complexity had significant associations with the Calculus and Physics course grades (*r* range = .14 to .36). No correlation was significant with General Chemistry. Thus, Hypothesis 11, which stated that STEM Interest Complexity would be moderately correlated with STEM achievement indices, was partially supported, with some small or non-significant correlations. In the entire sample, all STEM interest complexity scales correlated significantly with the STEM courses, including Chemistry (*r* range = .18 to .41).

Table 9.16 Concurrent Criterion-related Validation of the STEM Interest Complexity Scales: Academic Achievement Indices

Measures	STEM GPA (Stem *N*=151) (All *N*=224)	Calculus1 (Stem *N*=73) (All *N*=113)	Calculus2 (Stem *N*=134) (All *N*=167)	Physics1 (Stem *N*=103) (All *N*=123)	Chemistry (Stem *N*=105) (All *N*=132)
Numeric					
Stem major	.21*	.21	.24**	.23*	.01
All sample	.30**	.35**	.31**	.32**	.20*
Symbolic					
Stem major	.27**	.14	.26**	.36**	.06
All sample	.34**	.34**	.34**	.41**	.23**
Spatial					
Stem major	.21**	.21	.17*	.21*	.01
All sample	.21**	.29**	.20*	.25**	.18*
Ideas					
Stem major	.27**	.18	.19*	.21*	.11
All sample	.34**	.30**	.21**	.27**	.24**
General					
Stem major	.27**	.14	.24**	.20*	.10
All sample	.32**	.31**	.27**	.25**	.23**
STEM interest complexity composite					
Stem major	.32**	.22	.26**	.31**	.07
All sample	.34**	.36**	.31**	.36**	.24**

Notes. STEM: Science, Technology, Engineering, and Mathematics; GPA: Grade Point Average.
* $p < .05$; ** $p < .01$.

9.2.2.2.4 Hypothesis 12. Relative Importance of Vocational Measures

I hypothesized that STEM Interest Complexity would contribute more to the prediction of vocational criteria than would the relevant RIASEC interests and self-concept measures. This hypothesis was tested with a series of dominance analyses. Composite variables using unit-weighted z-scores were formed for each type of assessment. Direction of interest was based on a composite of realistic and investigative interests; self-concept composite was formed by combining math and science self-concept scores; and level of interests (i.e. STEM Interest Complexity) was based on a composite of numeric, symbolic, spatial, and ideas scales. Seven dominance analyses were run for each vocational criterion. Predictor intercorrelations and correlations with criteria are presented in Table 9.17.

Table 9.17 Correlations between Interest Assessments and Vocational Criteria

	1	2	Stem GPA	Stem BS intent	Stem Grad intent	Stem Career intent	Major Sat	Acad Sat	Occ Level
1. Interest Composite	1.00		.017	.189**	.187**	.193**	.140*	.045	.177**
2. Self-concept composite	.201**	1.00	.184*	.253**	.124**	.224**	.332**	.322**	.217**
3. STEM interest complexity Composite	.376**	.501**	.279**	.313**	.193**	.392**	.352**	.288**	.327**

Notes. Correlations are based on the STEM major sample (N = 151 on GPA, N = 269 on variables related to intentions to pursue a STEM field, and N = 274 on the remaining self-report measures). STEM: Science, Technology, Engineering, and Mathematics; GPA: Grade Point Average; Grad: graduate degree; Sat: satisfaction; Acad: academic; Adj: adjustment; Occ Level: vertical career intentions. * $p < .05$; ** $p < .01$.

First, each predictor was correlated with the criteria and the percent of shared variance was reported. Then, subsets predictors were each regressed on the criteria and the percent of shared variance was reported. Then, the additional contribution of each predictor over each of the other predictors, and over the pair of predictors, was computed. Finally, each predictor's contribution over every other predictor and the pairs of predictors was averaged to arrive at the relative importance of that variable in the prediction of a criterion. The values at each step of the dominance analyses are presented in Appendix J (see Table J6.1 through J6.7). The relative contribution of each variable is presented in the bottom row marked "overall average."

The relative contribution of the direction of interests (i.e. Realistic+Investigative) explained between 0% and 3% of the variance in criteria. The relative contribution of self-concept (i.e. Math and Science) explained between 1% and 7% of the variance. Finally, the relative contribution of level of interests (i.e. STEM Interest Complexity) explained between 2% and 12% of the variance. Hypothesis 12 was supported. The relative contribution of each assessment is presented in Table 9.18. Interest complexity had the highest relative contribution for each subset regression model across the criteria, except for STEM graduate degree intentions and academic adjustment.

Table 9.18 Relative Contribution of Vocational Interest Assessments

	STEM GPA	STEM BS Intent	STEM Grad Intent	STEM Career Intent	Major Satisfac-tion	Academic Adjust-ment	Occupa-tional Level
Direction of Interests	.005	.018	.024	.017	.008	.003	.015
Self-concept	.015	.035	.007	.023	.069	.073	.024
Level of Interests	.067	.062	.020	.117	.080	.054	.076

Notes. Values indicate the percent of variance shared with the criteria. STEM: Science, Technology, Engineering, and Mathematics; GPA: Grade Point Average; BS: Bachelor of Science; Grad: graduate.

CHAPTER X

DISCUSSION ON THE NEW VOCATIONAL INTEREST ASSESSMENT: STEM INTEREST COMPLEXITY MEASURE

The discussion on the STEM Interest Complexity scales starts with an overall summary of the basic characteristics of the measure, including differentiation between complexity levels, factor structure, college major differences, and preliminary support provided in Study 1. Then, results pertaining to construct and criterion-related validation are discussed. Finally, the contribution to the literature is discussed together with future directions and the limitations of the present study.

10.1 Overview of the STEM Interest Complexity Measure

The purpose of developing the STEM Interest Complexity scales was to differentiate between interest in STEM field tasks that have low, moderate, and high levels of complexity. Scale means obtained both in Study 1 and Study 2 indicated that low-complexity items received higher ratings of interest than moderate and high-complexity items. Levels of interest in the moderate- and high-complexity scales were similar to each other. This trend was observed in both the STEM and non-STEM samples.

Factor analyses supported the four content factors of numeric, symbolic, spatial, and ideas. Study 2 confirmatory factor analysis also provided support for having complexity levels, as indicated by the fact that the better fitting model included the complexity scales. Testing for the bifactor model indicated that most of the variance in responses was captured by the global STEM interest factor. This finding indicated that the measure is a coherent and contained one with which to assess interests within the STEM domain, and that the scales can be used jointly. The finding that moderate- and high-complexity scales have higher loadings on the global STEM interest factor than do the low-complexity scales further indicated that the global factor is a construct that reflects interests towards more complex tasks. Hence, moderate- and high-complexity levels are more relevant for the STEM fields which are rated as the most complex and demanding occupations within the realistic and investigative themes.

Analysis of group differences revealed that STEM majors showed higher interests on all domains and all complexity levels than did the non-STEM and transfer groups. The effect sizes of these differences were large, based on Cohen's (1988) criteria of effect sizes. When compared to the traditional interest assessments, the STEM Interest Complexity scales had larger group differences.

Initial investigation of the STEM Interest Complexity scales in Study 1 provided preliminary support for the use of the new measure. The new measure had significant small to moderate associations with realistic and investigative interests; math, science, and spatial self-concept; cognitive abilities; and various vocational criteria. Overall, Study 1 results indicated that the magnitude of associations between outcomes and the numerical, symbolic, and ideas scales was higher than between outcomes and the traditional interests assessments. A composite of the moderate- and high-complexity numeric, symbolic, and ideas scales was used to predict STEM-GPA and intentions to further pursue a STEM BS, graduate degree, and career. Results showed that this interest complexity composite added between 5% and 10% variance over and above the traditional interest assessments. Specific hypotheses were formed to be tested in Study 2 adding several more vocational criteria and theoretically-related constructs. Results obtained in Study 2 provided either partial or full support for all the hypotheses, further supporting the validity of the new measure. All analyses for the STEM complexity domains were carried out based on a composite of moderate- and high-complexity scales.

10.2 Construct Validation

Construct-related validation was supported based on the results of Hypotheses 1 through 6. The STEM Interest Complexity scales were expected to measure both the direction and level of vocational interests. Their ability to assess the direction of interests was shown based on their moderate associations with the RIASEC themes, assessed with the UNIACT, that pertain to STEM areas. Numeric interests mapped onto conventional interests, spatial interests mapped onto realistic interests, and ideas and general STEM interest complexity scales both mapped onto investigative interests, all with strong correlations. Symbolic interests had moderate correlations across these three interest themes. The artistic, social, and enterprising themes had non-significant or very small associations with the interest complexity scales. Participants' self-concept ratings in the areas of math, science, spatial, and verbal tasks were also collected as a proxy to self-efficacy ratings in similar domains, which have typically been used in vocational counseling. Math and science self-concept had moderate to strong associations across the domains. Spatial self-concept mapped specifically onto spatial interests. Verbal self-concept had small significant negative correlations with all the interest complexity scales.

Gottfredson (1986) showed that as the complexity of an occupational class increases, the demand for cognitive abilities also increases. Thus, it was expected that those who have higher levels of cognitive abilities would also show higher levels of preference for more complex tasks. Both Study 1 and Study 2 findings revealed a moderate association between interest complexity and math abilities as indicated by SAT Math and the ETS Kit math scores. Spatial abilities also had a moderate association with spatial interests. Contrary to expectations, verbal abilities did not correlate with any of the complexity scales. However, Gottfredson's occupational aptitude map suggests that effective performance in more complex occupations also requires a high level of verbal ability. Perhaps the tasks dealt with in an organizational setting are more varied and require verbal abilities, but an interest in specifically STEM-related complex tasks is unrelated to verbal ability. Associations between abilities and interest complexity within the STEM sample were smaller than the ones observed in the entire sample. Perhaps this was because the STEM sample had a more restricted range of responses on interest complexity than did the entire sample.

Several theoretically-related constructs were hypothesized to be moderately associated with interest complexity. The complexity scales had moderate associations with typical intellectual engagement and learning-goal orientation. TIE refers to a person's desire to engage in cognitively engaging and complex work. Moderate associations with the complexity scales within the STEM sample supports the assertion that interest complexity assesses interests to engage in increasingly complex work. Learning-goal orientation also had moderate associations with the interest complexity scales, supporting the assertion that individuals who have the motivation to exert further effort in learning and mastering a challenging task and to persist in times of failure, also tend to attempt more complex and challenging tasks. This association was not limited to the individual's chosen field of study. Non-STEM majors who had higher levels of learning-goal orientation also showed higher levels of STEM interest complexity. Performance-avoidance orientation only had small significant associations with the symbolic and spatial scales. It appears that the feeling of inability to excel or make improvements on a task somewhat shows itself when it comes to dealing with complex symbolic or spatial tasks, but not with numerical tasks or STEM-related ideas. All three constructs (i.e. cognitive abilities, TIE, learning-goal orientations) shared between 14% and 38% variance with the interest complexity scales, supporting the assertion that the STEM Interest Complexity scales assess interest in engaging in increasingly complex tasks that are cognitively more demanding.

10.3 Criterion-related Validation

STEM Interest Complexity scales were expected to be associated with vocational criteria, which have typically been the focus of interest assessments. Support was found for moderate associations between the STEM Interest Complexity scales and vocational criteria: STEM membership, STEM major satisfaction and academic adjustment, achievement in STEM-related coursework in college, attachment to a STEM major as indicated by intentions to persist in and further pursue STEM-related fields, and several experiential variables related to engaging in STEM-related work in high school and college. All of these vocational criteria were also correlated with the traditional forms of interest assessments to compare these associations with those of the newly developed complexity scales.

Construct validation of the scales provided initial support for the assertion that STEM Interest Complexity scales assess both the direction of interests (as indicated by their associations with the relevant RIASEC themes) and the level of interests (as indicated by their associations with cognitive abilities, TIE, and learning goal orientations). Further support showing that the measure assesses the direction of vocational choice came from the correct prediction of current major membership, and support that the scales assess the level of vocational choice came from the study of participants' intentions to pursue a complex occupation.

Both Study 1 and Study 2 results revealed that the STEM Interest Complexity scales predict STEM versus non-STEM major membership with moderate effect sizes. In the present study, realistic and investigative interests and math and science self-concept had a smaller effect size in discriminating between STEM and non-STEM majors. Interest complexity scales also significantly discriminated between STEM participants and the group of participants who transferred from a STEM to a non-STEM major. The effect size was small, but higher than that of the traditional interest assessments. It was observed that, on the interest complexity function, the transfer group equally shared characteristics with the STEM and non-STEM groups, which makes discrimination difficult. The predictive value of the STEM Interest Complexity scales was also shown by the significant amount of incremental variance they added over and above the traditional forms of assessment in predicting STEM membership.

Further support for how well the STEM Interest Complexity measure could assess the level of vocational choice came from the associations with participants' intentions to choose a complex occupation. Interest complexity scales had moderate associations, whereas the traditional assessments had small associations with intentions to choose a complex occupation, indicating that the complexity scales may also better predict actual career choices students will make in the future.

Further concurrent criterion-related validation of the STEM Interest Complexity scales was carried out by correlating the scales with several vocational criteria such as major satisfaction, performance, and persistence in and attachment to the chosen academic field, all of which have been traditionally used to show that an interest assessment is valid (e.g., Bruch & Krieshok, 1981; Lindley & Borgen, 2002; Tracey & Robbins, 2006). Both Study 1 and Study 2 results suggested that the STEM Interest Complexity scales were mostly moderately associated with self-reported intentions to persist in and further pursue a STEM-related field. Moderate associations with the intentions to pursue a STEM graduate degree were obtained only in Study 1. Study 2 correlations were still significant, but they were mostly in the smaller range. Both studies yielded moderate associations between intentions to pursue a career in a STEM field and the interest complexity scales.

To further assess attachment to STEM fields, several experiential questions were asked relating to participants' high school and college experiences. Even though moderate associations were expected between such experiential variables and the interest complexity scales, small significant associations were obtained at best, and results were not consistent across Study 1 and Study 2. In Study 1, all moderate- and high-complexity scales were significantly associated with high school STEM competition and club participation, and the age at which participants first decided to pursue a STEM field. Symbolic interests were also significantly associated with the number of science courses taken in high school. None of these variables were significant in Study 2. The only variable that yielded significant associations in Study 2 was STEM activity participation at the college level. All interest scales, except for numeric interests, were significant. Since the STEM sample results were not consistent across studies, the relationship between interest complexity and attachment to STEM is not conclusive for the STEM participants. Even though the STEM sample correlations were mostly not significant in Study 2, the entire sample correlations, including the non-STEM and transfer groups, were mostly significant across both studies, which lends support to the expected association between the level of interest complexity and STEM field attachment.

Interest complexity was also correlated with STEM major satisfaction and adjustment to academic life in Study 2. As expected, moderate associations were obtained with the STEM Interest Complexity scales. Correlations with STEM major satisfaction were slightly higher than those with academic life adjustment. This slight difference could be attributed to the match between the content of the interest complexity scales and the typical curricular tasks undertaken in STEM majors.

Finally, the STEM Interest Complexity scales were correlated with academic achievement indices of STEM-GPA and grades in specific STEM courses (e.g. calculus, physics, chemistry). Significant small to moderate associations were observed with STEM-GPA. Within the STEM sample, the highest associations were observed with symbolic interests, followed by ideas. When specific course grades were explored, the most consistent associations across courses were observed with symbolic and numeric interests, especially for the Calculus and Physics courses. Spatial interests were mostly associated with Physics. Ideas and general STEM interest complexity were not consistently associated with any of the studied course grades within the STEM sample. Perhaps ideas was correlated with STEM-GPA based on grades obtained in more research-oriented STEM courses.

Correlations were again observed to be higher in the entire sample as compared to the STEM sample. All interest complexity domains were moderately associated with STEM-GPA and Calculus 1, 2, and Physics 1 grades, and had small significant associations with Chemistry grades. The association between academic achievement and interest complexity becomes apparent when the range of grades and scores on the complexity scales is less restricted.

What is more important from a counseling perspective is whether or not the STEM Interest Complexity adds significant incremental variance over the traditional assessments of the direction of interests and self-concept measures in the prediction of vocational criteria. Hierarchical regression analyses were conducted in Study 1. The STEM Interest Complexity composite added from 5% to 10% variance over and above the traditional forms of assessments in the prediction of STEM-GPA and persistence. Beta coefficients were all significant and had moderate effect sizes. Self-concept scales added from 5% to 10% incremental variance over realistic and investigative interests. The percent of variance that these two interest themes shared with the criteria ranged from 0% to 5%, which is consistent with the review of Spokane et al. (2000), suggesting that interests shared 5% of variance with academic success, persistence, and satisfaction.

To investigate the relative importance of each type of interest assessment, series of dominance analyses were conducted in Study 2. It was hypothesized that the STEM Interest Complexity scales would contribute more to the prediction of vocational criteria than did an assessment of only the direction of interests. As expected, the most important type of interest assessment in predicting vocational criteria was interest complexity, with shared variances ranging from 2% to 12%. For all vocational criteria, except for adjustment in academic life and intentions to further pursue a STEM graduate degree, the contribution of interest complexity (ranging from 6% to 12%) was higher than the contribution of self-concept or the realistic and investigative interests in all subset regression models and in terms of the average. Self-concept's relative importance came second, with shared variances ranging from 1% to 7%. Realistic and investigative interests had shared variances ranging from 0% to 2%. Assessing the level of vocational interests contributed more to the prediction of vocational criteria, which implies that incorporating level of interest assessments in vocational counseling would greatly improve criterion-related validities.

10.4 A Summary on the New Measure's Content Domains

Complexity of interests geared towards STEM areas was assessed based on four contents and the general STEM interest complexity scale. At this point, a summary of how each of these scales differentially relate to the vocational criteria is warranted. Numeric interests, symbolic interests, ideas, and general STEM interest complexity had more or less similar patterns and magnitudes of associations across the achievement indices of STEM-GPA and course grades. In STEM membership discrimination, ideas was the best predictor, followed by symbolic and numeric interests. Ideas played the biggest role particularly in the discrimination of transfer participants from the STEM participants. In terms of major satisfaction and the variables indicating intentions to persist in and pursue a STEM field, ideas and general STEM interest complexity had the highest associations. These two scales and symbolic interests also had significant associations with STEM attachment indicators, though only at the entire sample level. Spatial interests, for the most part, had significant but lower associations with all the criteria, except for the STEM attachment indicators.

Despite slight differences in the patterns of associations across the four contents, the composite variable including all four domains yielded moderate correlations with academic achievement, major satisfaction, academic adjustment, intentions to persist in and further pursue STEM areas, and intentions to work in a complex STEM occupation. This composite was also the most important contributor to these criteria when compared to the traditional assessments. The bifactor confirmatory analysis indicated a global STEM interest factor, with these four domains adding little specific variance over the global factor. This finding also supports the use of a composite in studying validities of the new instrument.

The general STEM interest complexity scale, which was shorter, also had moderate associations with achievement, persistence, and satisfaction. This scale's pattern of associations was very similar to that of the ideas scale. It can be argued that the scale can be used if a shorter scale is desired, when investigations do not warrant exploring content domain differences in relation to outcomes.

10.5 Importance of the Study Findings and Contribution to the Literature

The present study findings strongly support the assertion that assessing the level of interests in addition to the direction of interests improves criterion-related validities. There has been a vast emphasis on the assessment of the direction of vocational interests for determining person-occupation fit, stemming from the idea that individuals seek and happily remain in work environments that would fit their interests (Holland, 1985). However, some scholars have pointed out that the validities of such assessments range from weak to moderate (Spokane et al., 2000). Paterson, Darley, and Elliot (1936) and Super (1957) viewed the assessment of abilities as an integral part of vocational counseling. More recently, several other scholars have also pointed to the importance of cognitive assessments in career counseling and also noted that individuals' levels of abilities and skills do not receive much attention in vocational counseling assessments (Austin & Hanish, 1990; Converse, Oswald, Gillespie, Field, & Bizot, 2004; Gottfredson, 2003; Gottfredson & Richards, 1999; Tinsley, 2000; Tracey & Hopkins, 2001). Such arguments stem from the well documented finding that abilities play a role in job performance (e.g., Schmidt & Hunter, 1998), especially in more complex occupations, and that different occupations require differential levels of minimal abilities for effective job performance (Gottfredson, 1986). The meta-analysis of Kristof-Brown et al. (2005) revealed that when the fit between job demands and individual abilities were incorporated into the person-job fit index, strong associations were observed with vocational criteria, such as organizational commitment, job satisfaction, tenure, and intentions to quit/remain.

The idea of incorporating ability assessments in vocational counseling is a rational one, since an individual's skill level is a factor determining his or her occupational interests (Ostroff, Shin, & Feinberg, 2002, *p*.69), and individuals tend to gravitate towards occupations that fit their competencies (Wilk et al., 1995; Wilk & Sackett, 1996). Using ability assessments in counseling would speed the process of gravitation; thus, individuals would be able to effectively use and express their skills and abilities on the chosen vocational track. Several self-evaluations, such as self-efficacy ratings, competency ratings, and ability self-estimates, have been integrated in vocational counseling assessments as a proxy to ability assessment (e.g. Betz, Borgen, & Harmon, 1996; Betz, Borgen, & Harmon, 2006; Campbell et al., 1992; Harmon et al., 1994; Holland, 1985; Holland, 1994; Kuder & Zytowski, 1991; Lent et al., 1987; Lindley & Borgen, 2002; Prediger & Swaney, 1995). Lent et al. (1994) have shown that interests develop based on an individual's self-efficacy in specific domains, and self-efficacy is shaped by prior exposure and level of achievement in those domains. However, empirical findings indicated that there are two problems with self-evaluations. Self-efficacy ratings, ability self-estimates, or self-estimates of knowledge are not necessarily a truthful reflection of an individual's ability level (Ackerman, Beier, & Bowen, 2002; Mabe & West, 1982). Moreover, there is no consistent finding in the literature indicating that self-evaluations improve the validities of vocational assessments (e.g., Lent et al., 1987; Prediger & Brandt, 1991; Tracey & Hopkins, 2001). Self-efficacy ratings were found to be correlated with work performance with low-complexity tasks rather than high-complexity tasks (Judge et al., 2007), which renders their usefulness questionable for identifying the appropriate level of vocations.

The STEM Interest Complexity scales developed and validated in the present study offer a promising proxy to assessing abilities. Even though the new measure does not assess abilities or even self-estimated abilities per se, it has been developed with a focus on measuring preferences to engage in more specialized and complex STEM area tasks. Items integrated into the assessment describe tasks which are a part of increasingly complex occupations, jobs which demand higher cognitive abilities. Moreover, the new measure had moderate associations with math and spatial abilities. Incorporating more specific tasks with increasing complexity results in an assessment with higher fidelity, one that reflects the work demands more realistically. This way, individuals can evaluate their work preferences using task descriptions that are most representative of the basic nature of the work they would be interacting with in college or on the job.

The higher fidelity of the new measure distinguishes it from the most widely used model of interest assessment based on the RIASEC themes. Such traditional assessments (Swaney, 1995; O*NET, 2006) incorporate very generalized items that are ambiguous in terms of the task complexity and required level of cognitive abilities. Individuals' self-ratings on such scales do not align well with their preferences for tasks they will encounter in actual academic or work contexts; therefore, assessing the direction of interests does not show validities as high as does the new measure of interest complexity.

Item specificity and scale fidelity of the new measure was achieved by developing the assessment instrument based on information obtained from the occupation classification databases. Converse et al. (2004) emphasized that the O*NET database provides a comprehensive source of occupational information which should be consulted when matching individuals to occupations. Following up on the recommendation of

Converse et al., the O*NET and also the DOT were consulted in developing the new measure of STEM Interest Complexity. Information in O*NET was used to determine the low-, moderate-, and high-complexity occupations under the relevant Holland themes. Information as to the required skills, abilities, and typical work activities that distinguish these three complexity levels was also based on information obtained from O*NET. Such information was used in describing high fidelity tasks in the items. More detailed information was obtained from the DOT. DOT provided information about which occupations were complex in terms of dealing with data. Furthermore, it provided information about the types of engagement with data and each type's corresponding level of cognitive complexity (e.g., comparing data has a lower complexity level than does analyzing data, and analyzing has a lower complexity level than does synthesizing data). Such information was again incorporated in the scale in order to create descriptions of less complex and more complex tasks. By focusing on occupational task descriptors that fall under the realistic and investigative themes, the direction of interests was maintained, and incorporating the varying levels of task complexity added level of interests. The assessment therefore aligns well with the vertical classification of occupations.

Overall, the present study results indicate that vocational interest inventory validities can be improved by focusing on levels of occupational complexity. This study only focused on STEM areas; nevertheless, it offers a viable method to develop similar assessments for other work environments in which occupations differ in terms of complexity level. In vocational counseling practices, once the overall direction of interest is determined for an individual, a supplementary assessment could be administered to determine the level of interest within that work environment.

10.6 Limitations and Future Work

The present study was conducted with an undergraduate student sample from Georgia Tech. Most hypotheses were tested within the STEM sample, which is restricted in terms of level of interest complexity and STEM achievement. Even though the expected moderate associations were observed for the most part, the magnitude of associations could be larger in the more general student population than it was in the present study sample. The fact that the entire sample correlations were higher supports this claim. Thus, further support, based on more heterogeneous samples, is needed for the STEM Interest Complexity scales' associations with the vocational criteria.

Statistical power was adequate in the present study to investigate associations within the STEM sample and the entire sample. Nevertheless, the non-STEM sample and especially the transfer sample were much smaller, specifically on variables such as STEM-GPA and specific course grades. Exploring the transfer students would be more important in order to gain insight into their characteristics and the role of interest complexity in changing a major. Larger samples would enable such investigations. In addition to this special group, larger samples of participants enrolled in various STEM majors would also provide an opportunity for more in-depth analysis of sub-STEM majors (i.e. engineering, physical and biological sciences, computer science, math).

In this study, the new measure better predicted STEM-related vocational criteria than did the traditional assessments. This study adopted a concurrent validation design; therefore, the measure needs to be validated with a longitudinal study design before concluding that it can predict future college/occupation fit, success, and persistence in STEM areas.

Another issue that needs further attention and research is the educational level at which it would be most appropriate to use such a measure for counseling purposes. With their social-cognitive career process theory, Lent et al. (1994) suggested that developing differentiated self-efficacy about various subjects and possible interest in these subjects is a dynamic process that requires experience with such subjects. Even though most counseling takes place in high school, students may not have developed the insight to evaluate their preferences concerning the engagement in increasingly complex tasks at that level. If this is the case, either the scale will need to be refined to suit the high school level, which could decrease fidelity, or it could be used at the college freshman level when some students are still in the process of trying to select a major. At the college level, students will be exposed to STEM-related courses that would give them an idea of whether they further want to engage in such tasks. While the four STEM Interest Complexity scales could be administered at the college entry level, administering the general STEM interest complexity scale at the high school level could yield more promising results.

Finally, the present study did not explore the hypothesized associations within genders. A recent meta-analytic investigation points to gender differences in terms of Holland's interest themes and STEM subject interests (Su, Rounds, & Armstrong, 2009). Large differences were found for realistic interests and engineering interests, with men showing a higher preference than women. Small differences were found for investigative, science, and math interests, again with men indicating a higher preference than women. The STEM Interest Complexity scales need to be investigated for possible gender differences and the way in which the scales relate to criteria within each gender.

CHAPTER XI

CONCLUSIONS

The objective of conducting the present study was to further explore the non-ability traits of the science/math trait complex. The trait complex approach (Ackerman & Heggestad, 1997) makes it possible to study the individual holistically by taking into account various domains of individual differences—such as abilities, personality, motivation, and vocational preferences—at the same time. Most up-to-date research investigating the role of individual differences in relation to educational or work outcomes have focused on these domains separately. For instance, in the vocational psychology literature, individuals' preferences to work in certain environments has been the primary focus in understanding why individuals chose and were satisfied in certain vocational tracks. Some theoretical propositions have been made about what role other individual differences (i.e. cognitive abilities and personality) play in the development of vocational interests, but these separate domains were not studied together. Similarly, in the organizational psychology literature, where investigating the predictors of employee performance has been the main goal, cognitive abilities and personality factors have typically been studied independently.

Nonetheless, the literature reports significant associations between the intellectual, affective, and conative traits (e.g., Barrick, Mount, & Gupta, 2003; Carless, 1999; Wolf & Ackerman, 2005). Ackerman (Ackerman, 1997; Ackerman & Heggestad, 1997) claimed that such traits, which are conceptually distinct, develop over time by shaping each other, and ultimately their joint effect (a trait complex) determines an individual's vocation and work-related decisions and outcomes. Empirical evidence has been provided concerning the advantages of studying an individual holistically based on trait complexes when predicting educational and work outcomes (Ackerman, 2003; Kanfer et al. 2010). The main objective of the present study was to further explore the non-ability markers of the science/math trait complex. Kanfer et al. (2010) showed that non-ability trait composites add significant incremental variance over cognitive abilities in the prediction of educational and work outcomes, which supports the present study's objective.

In line with this objective, two studies were conducted, one searching for the personality correlates of the science/math trait complex, and the other one revisiting the nature of vocational interests which the engineering and scientist groups tend to posses. Investigation results indicated that four different personality constructs and vocational interest complexity were associated with the science/math trait complex and related vocational criteria. The most important conclusions of this research are presented as follows, together with the study's limitations and future directions:

1) Toughmindedness is the personality marker of the science/math trait complex.
2) Toughmindedness, cognitively-oriented behavior, achievement, and control have differential associations with STEM-related vocational criteria. Toughmindedness is associated with intending to pursue a STEM-related career. Cognitively-oriented behavior is associated with more challenging and cognitively demanding pursuits such as an intention to pursue graduate level STEM education and participation in STEM-related competitions. Achievement and control are related to academic curricular achievement in STEM.

3) Utilizing a trait complex approach in predicting outcomes is further supported by the significant associations between the science/math trait complex and vocational criteria.
4) Non-ability individual differences, in addition to abilities, significantly contribute to the prediction of vocational criteria.
5) The new STEM Interest Complexity Measure, which assesses preferences for engaging in increasingly complex tasks in the numerical, symbolic, spatial, and ideas domains, has good construct and concurrent criterion-related validities.
6) Assessing the direction of interests does not give an adequate representation of STEM member interests. Present study results yielded evidence as to the predictive value of assessing the level of interests in addition to the direction of interests. Level of interests, which in the present study was defined as the level of task complexity one wishes to attempt, had the highest relative contribution to predicting STEM-related vocational criteria, higher than the traditional forms of interest assessments (i.e. direction of interests and self-evaluations). Results point out that the validity of vocational interest assessments can be improved by incorporating level of interests.
7) Generalizability of the study findings to wider college student populations is limited because the study sample was restricted in terms of several variables such as interest complexity and achievement. Further investigation into the STEM personality correlates and interest complexity scales, based on more heterogeneous samples of college students, is needed.

8) The present study sample did not have an equivalent representation of students from various STEM majors. Future studies need to sample adequately from different STEM majors in order to utilize hierarchical modeling techniques.
9) Study results cannot be generalized to high school student populations. Further research is needed to explore whether or not the newly developed interest complexity measure would apply to the high school level.
10) Gender differences were not a focus of the present study. The literature points to consistent gender differences in Holland interests and specific abilities. Therefore, future studies need to investigate whether or not personality or interest complexity have different patterns of associations with criteria across the genders.

APPENDIX A

SUMMARY OF STUDIES THAT INVESTIGATED PERSONALITY CHARACTERISTICS OF ENGINEERS

Summary of Studies that Investigated Personality Characteristics of Engineers

Source	Personality Factor	Result for Engineers	Statistical Results (mean, sd, t-test)	Cohen's *d*	Hedges' $\hat{g}$	Assessment Instrument	Sample Characteristics	Comparison Group
A Preference for Things and Structure								
Williams (1997)	• Extraversing • Outgoing • Introversing • Retiring	Low Low High High	t = -4.00 (males) t = -3.75 (males) t = 4.70 (males) t = 3.91 (males)	**-0.454** **-0.426** **0.534** **0.444**	**-0.452** **-0.424** **0.532** **0.442**	The Millon Index of Personality (MIPS; Millon, 1994)	86 male and 72 female freshmen engineering students	MIPS normative sample (800 male and 800 females college students, only 1.5% were engineers)
Izard (1960)	• Intraception • Nurturance • Affiliation • Deference • Order	Low Low Low Low High	No descriptive statistics available	NEGATIVE AFFECTIVITY	NA	Edwards Personal Preference Schedule (EPPS)	173 freshman engineers	173 **male** freshmen in arts and sciences
Izard (1960)	• Abasement • Affiliation • Intraception • Nurturance	Low Low Low	No descriptive statistics available	NEGATIVE AFFECTIVITY	NA	EPPS	81 employed engineers	750 **male** liberal arts students
Harris (1994)	• Need for Cognitive Structure	High	No descriptive statistics available	NEGATIVE AFFECTIVITY	NA	Personality Research Form	66 Engineering, nursing, and psychology students	Nursing and psychology students
Brown & Joslin (1995)	• Uncomfortable for uncertainty • Uncomfortable for complexity • Uncomfortable for organization	High High High	No descriptive statistics available	NEGATIVE AFFECTIVITY	NA	Adjective Check List (Gough & Heilburn, 1980)	78 engineering undergraduates (39 men and women)	College norms for the Adjective Check List (261 women, 262 males)

Source	Personality Factor	Result for Engineers	Statistical Results (mean, sd, t-test)	Cohen's *d*	Hedges' $\hat{g}$	Assessment Instrument	Sample Characteristics	Comparison Group
A Preference for Thinking as opposed to Feeling								
Williams (1997)	• Accomodating	High	Males: t = 2.30	Males: **0.261**	Males: **0.260**	Millon Index of Personality Styles	86 male and 72 female freshmen engineering students	MIPS normative sample (800 male and 800 females college students, only 1.5% were engineers)
		Low	Females: t = -2.08	Females: **-0.256**	Females: **-0.234**			
	• Thinking	High	Females: t = 4.47	Females: **0.550**	Females: **0.503**			
	• Nurturing	Low	Females: t = -2.17	Females: **-0.267**	Females: **-0.244**			
	• Intuiting	Low	Females: t = -2.03	Females: **-0.283**	Females: **-0.228**			
	• Feeling	Low	Females: t = -4.07	Females: **-0.501**	Females: **-0.458**			
	• Agreeing	Low	Females: t = -3.05 (df = 870)	Females: **-0.376**	Females: **-0.345**			
Harris (1994)	Nurturance	Low	No descriptive statistics available	NEGATIVE AFFECTIVITY	NA	Personality Research Form	14 upper year Engineering students = 14 (female = 4)	22 Upper year Nursing students

Source	Personality Factor	Result for Engineers	Statistical Results (mean, sd, t-test)	Cohen's *d*	Hedges' $\hat{g}$	Assessment Instrument	Sample Characteristics	Comparison Group
Toughmindedness, Stability, & Self-sufficiency								
Goodman (1942)	• Neuroticism (Emotional Stability)	High	Engineers: M = 199.90, sd = 72.40 Arts: M = 233.90, sd = 81.20	**-.441**	**-.45**	Bernreuter Personality Inventory (Bernreuter, 1931)	237 **male** freshmen engineers	166 **male** freshmen liberal arts students
	• Self-Sufficiency	High	Engineers: M = 254.90, sd = 43.20 Arts: M = 241.30, sd = 49.40	**0.293**	**.30**			
Izard (1960)	• Dominance • Succorance	High Low	No descriptive statistics available	NEGATIVE AFFECTIVITY	NA	EPPS	173 **male** freshman engineers	173 **male** freshmen in arts and sciences
Kline & Lapham (1992)	• Conventionality	High	Engineers: M = 5.63 Arts: M = 4.31 Social sciences: M = 4.92	NEGATIVE AFFECTIVITY	NA	Professional Personality Questionnaire (Kline & Lapham, 1990)	N = 1472 undergraduates from different faculties and universities (Engineers = 62, Science students = 326). Gender distribution not reported by faculty.	Arts students (N = 357) Social sciences (N = 557)
	• Tough-mindedness		Engineer = 6.45 Science = 5.68 Social sci = 5.65 Arts = 4.85 **Std dev. not provided**					
Harris (1994)	• Need of Autonomy	High	No descriptive statistics available	NEGATIVE AFFECTIVITY	NA	Personality Research Form	66 Engineering students	Nursing and psychology students

Source	Personality Factor	Result for Engineers	Statistical Results (mean, sd, t-test)	Cohen's *d*	Hedges' $\hat{g}$	Assessment Instrument	Sample Characteristics	Comparison Group
Toughmindedness, Stability, & Self-sufficiency								
Brown & Joslin (1995)	• Autonomous • Assertive • Competitive • Determined • Dominance • Personal Adjustment • Self-confidence • Stubborn • Awareness of self-concern • Communality • Femininity • Temperamental	High High High High High High High High Low Low Low Low	No descriptive statistics available	NEGATIVE AFFECTIVITY	NA	Adjective Check List	Engineering students	College norms for the Adjective Check List
Achievement Motivation and Endurance								
Izard (1960)	• Achievement • Endurance	High High	No descriptive statistics available	NEGATIVE AFFECTIVITY	NA	EPPS	173 freshman engineers	173 **mal**e freshmen in arts and sciences
Harris (1994)	• Need of Achievement • Endurance	High High	No descriptive statistics available	NEGATIVE AFFECTIVITY	NA	Personality Research Form	Engineering students	Nursing and psychology students
Brown & Joslin (1995)	• Achievement	High	No descriptive statistics available	NA	NA	Adjective Check List	Engineering students	College norms for the Adjective Check List
Intellectance, Cognitive Styles, Learning Styles								
Barrett & Thornton (1967)	Field-independent	High	Engineers: M = 8.1, sd = 5.1 Standardization sample: M = 12.4, sd= 7.4	**-0.68**	**-0.67**	Rod-and-Frame Test	46 employed **male** engineers and technicians	Witkin's standardization sample (all males)

APPENDIX B

DIFFERENCES BETWEEN ENGINEERS AND OTHER VOCATIONS BASED ON CPI AND 16PF

CPI Student Samples

				Comparison with the engineering sample	
CPI factor	Mean	Std Dev	Sample Size	**Cohen's *d***	**Hedges $\hat{g}$**
Tolerance					
Engineering Sample	24.88	3.13	66		
General population	22.36	4.18	3235	**0.68**	**0.61**
Architect	22.25	3.84	125	**0.75**	**0.73**
Education	25.19	3.32	167	**-0.10**	**-0.09**
Premedical	25.8	2.94	70	**-0.30**	**-0.30**
Artistic	18.43	4.44	44	**1.68**	**1.73**
Military	22.08	4.01	1413	**0.78**	**0.70**
Achievement-via-Conformance					
Engineering Sample	29.32	4.63	66		
General population	27.74	4.71	3235	**0.34**	**0.34**
Architect	27.04	5.02	125	**0.48**	**0.49**
Education	30.33	3.92	167	**-0.24**	**-0.24**
Premedical	31.84	3.36	70	**-0.62**	**-0.62**
Artistic	19.7	4.22	44	**2.17**	**2.14**
Military	29.45	4.44	1413	**-0.03**	**-0.03**
Achievement-via-Independence					
Engineering Sample	26.53	3.43	66		
General population	23.83	4.63	3235	**0.66**	**0.59**
Architect	23.82	4.21	125	**0.71**	**0.68**
Education	26.94	3.82	167	**-0.11**	**-0.11**
Premedical	28.24	3.19	70	**-0.52**	**-0.51**
Artistic	22.89	4.72	44	**0.88**	**0.91**
Military	21.94	4.16	1413	**1.20**	**1.11**
Intellectual Efficiency					
Engineering Sample	33.45	3.61	66		
General population	31.52	4.54	3235	**0.47**	**0.43**
Architect	31.3	4.47	125	**0.53**	**0.51**
Education	33.93	3.45	167	**-0.14**	**-0.14**
Premedical	35.13	2.63	70	**-0.53**	**-0.53**
Artistic	28.23	5.05	44	**1.19**	**1.22**
Military	32.27	4.2	1413	**0.30**	**0.28**
Psychological-Mindedness					
Engineering Sample	19.42	2.9	66		
General population	16.62	3.32	3235	**0.90**	**0.85**
Architect	16.37	2.9	125	**1.05**	**1.05**
Education	18.75	2.91	167	**0.23**	**0.23**
Premedical	19.67	2.22	70	**-0.10**	**-0.10**
Artistic	15.36	3.22	44	**1.32**	**1.33**
Military	16.44	2.91	1413	**1.03**	**1.02**

CPI Student Samples _ Continued

CPI factor	Mean	Std Dev	Sample Size	Comparison with the engineering sample	
				Cohen's *d*	**Hedges $\hat{g}$**
Femininity/Masculinity[1]					
Engineering Sample	12.42	2.83	66		
General population	13.48	3.59	3235		
Architect	14.22	3.75	125	**-0.33**	**-0.30**
Education	13.88	3.36	167	**-0.54**	**-0.52**
Premedical	13.17	3.18	70	**-0.47**	**-0.45**
Artistic	16.48	4.11	44	**-0.25**	**-0.25**
Military	11.89	3.16	1413	**-1.15**	**-1.19**

Note. 1) Negative values indicate high Masculinity.

CPI Occupational Samples

CPI factor	Mean	Std Dev	Sample Size	Comparison with the engineering sample	
				Cohen's *d*	**Hedges $\hat{g}$**
Tolerance					
Engineering Sample	23.94	3.31	47		
Architects	23.91	3.48	124	**0.01**	**0.01**
Bankers	24.27	3.54	49	**-0.10**	**-0.10**
Business Executives	23.68	4	185	**0.07**	**0.07**
Correction Officer	20.49	4.51	221	**0.87**	**0.80**
Entrepreneurs	23.3	3.86	37	**0.18**	**0.18**
Mathematicians	25	3.6	57	**-0.31**	**-0.30**
Military	22.42	3.71	343	**0.43**	**0.41**
Police officers	21.84	4.43	366	**0.54**	**0.49**
Research Scientist	26.27	3.19	45	**-0.72**	**-0.71**
Sales Managers	22.45	3.78	85	**0.42**	**0.41**
Commercial Writers	23.07	4.98	14	**0.21**	**0.23**
Book Author	24.41	4.21	29	**-0.12**	**-0.13**
Achievement-via-Conformance					
Engineering Sample	31.06	3.33	47		
Architects	29.63	3.69	124	**0.41**	**0.40**
Bankers	30.24	3.58	49	**0.24**	**0.24**
Business Executives	29.92	4.46	185	**0.29**	**0.27**
Correction Officer	28.3	4.71	221	**0.68**	**0.61**
Entrepreneurs	30.16	3.28	37	**0.27**	**0.27**
Mathematicians	28.84	3.86	57	**0.62**	**0.61**
Military	29.44	4.03	343	**0.44**	**0.41**
Police officers	29.08	4.16	366	**0.53**	**0.48**
Research Scientist	30.29	3.37	45	**0.23**	**0.23**
Sales Managers	30.64	3.63	85	**0.12**	**0.12**
Commercial Writers	28.64	4.31	14	**0.63**	**0.67**
Book Author	27.28	4.03	29	**1.02**	**1.04**

CPI Occupational Samples _ Continued

				Comparison with the engineering sample	
CPI factor	Mean	Std Dev	Sample Size	**Cohen's *d***	**Hedges $\hat{g}$**
Achievement-via-Independence					
Engineering Sample	25.95	3.77	47		
Architects	25.31	3.88	124	**0.17**	**0.17**
Bankers	25.14	3.86	49	**0.21**	**0.21**
Business Executives	24.7	4.9	185	**0.29**	**0.27**
Correction Officer	21.11	4.64	221	**1.14**	**1.07**
Entrepreneurs	23.84	3.84	37	**0.55**	**0.55**
Mathematicians	28.65	3.68	57	**-0.72**	**-0.72**
Military	23.04	4	343	**0.75**	**0.73**
Police officers	23.05	4.68	366	**0.68**	**0.63**
Research Scientist	29.16	2.7	45	**-0.98**	**-0.97**
Sales Managers	21.84	4.01	85	**1.06**	**1.04**
Commercial Writers	24.57	3.41	14	**0.38**	**0.37**
Book Author	27.03	3.4	29	**-0.30**	**-0.29**
Intellectual Efficiency					
Engineering Sample	33.77	3.43	47		
Architects	32.55	3.54	124	**0.35**	**0.35**
Bankers	32.86	3.96	49	**0.25**	**0.24**
Business Executives	32.57	4.44	185	**0.30**	**0.28**
Correction Officer	30.04	4.82	221	**0.89**	**0.81**
Entrepreneurs	31.35	4.59	37	**0.60**	**0.60**
Mathematicians	34.12	3.98	57	**-0.09**	**-0.09**
Military	32.05	4.05	343	**0.46**	**0.43**
Police officers	30.36	4.22	366	**0.89**	**0.82**
Research Scientist	35.16	2.98	45	**-0.43**	**-0.43**
Sales Managers	31.93	3.97	85	**0.50**	**0.48**
Commercial Writers	37.64	4.03	14	**-1.03**	**-1.07**
Book Author	33.03	3.61	29	**0.21**	**0.21**
Psychological-mindedness					
Engineering Sample	19.55	1.94	47		
Architects	19.07	2.72	124	**0.20**	**0.19**
Bankers	17.8	3.2	49	**0.66**	**0.65**
Business Executives	18.26	3.02	185	**0.51**	**0.45**
Correction Officer	16.18	2.82	221	**1.39**	**1.25**
Entrepreneurs	16.84	2.96	37	**1.08**	**1.10**
Mathematicians	21.05	2.47	57	**-0.68**	**-0.66**
Military	17.07	2.64	343	**1.07**	**0.96**
Police officers	16.72	2.91	366	**1.14**	**1.00**
Research Scientist	22.16	2.64	45	**-1.13**	**-1.12**
Sales Managers	17.15	2.32	85	**1.12**	**1.09**
Commercial Writers	17.64	3	14	**0.76**	**0.85**
Book Author	18.69	2.98	29	**0.34**	**0.36**

CPI Occupational Samples _ Continued

CPI factor	Mean	Std Dev	Sample Size	**Comparison with the engineering sample**	
				Cohen's *d*	**Hedges $\hat{g}$**
Femininity/Masculinity[1]					
Engineering Sample	11.43	3.27	47		
Architects	15.61	3.06	124	**-1.32**	**-1.33**
Bankers	13.59	3.32	49	**-0.66**	**-0.65**
Business Executives	13.28	2.93	185	**-0.60**	**-0.61**
Correction Officer	13.14	2.94	221	**-0.55**	**-0.57**
Entrepreneurs	15.32	2.93	37	**-1.25**	**-1.23**
Mathematicians	16.53	3.09	57	**-1.60**	**-1.60**
Military	11.46	3	343	**-0.01**	**-0.01**
Police officers	12.05	2.73	366	**-0.21**	**-0.22**
Research Scientist	14.29	2.56	45	**-0.97**	**-0.96**
Sales Managers	12.85	2.93	85	**-0.46**	**-0.46**
Commercial Writers	15.57	2.9	14	**-1.34**	**-1.28**
Book Author	18.83	2.84	29	**-2.42**	**-2.35**

Note. 1) Negative values indicate higher masculinity.

				Comparison with the engineering sample	
16 PF	Mean	Std Dev	Sample Size	**Cohen's *d***	**Hedges $\hat{g}$**
Reasoning (B)					
Engineering Sample	8.2	1.9	77		
Executives	7.5	1.6	178	**0.40**	**0.41**
Sales Personnel	5	1.7	64	**1.78**	**1.76**
Employment Counselors	8.5	2.4	36	**-0.14**	**-0.14**
Social Workers	6.6	1.9	81	**0.84**	**0.84**
Mechanics	6	0.9	40	**1.48**	**1.34**
Electricians	6.6	1.8	67	**0.86**	**0.86**
Scientific Proffessions	9.8	0.8	144	**-1.10**	**-1.23**
Rule-Consciousness (G)					
Engineering Sample	6.3	1.7	77		
Executives	5.5	2.1	178	**0.42**	**0.40**
Sales Personnel	7.1	1.4	64	**-0.51**	**-0.51**
Employment Couns	4.5	2.3	36	**0.89**	**0.94**
Social Workers	5.1	1.8	81	**0.69**	**0.68**
Mechanics	5.5	1.8	40	**0.46**	**0.46**
Electricians	5.7	2	67	**0.32**	**0.32**
Scientific Prof	3.4	2.2	144	**1.48**	**1.42**
Abstractedness (M)					
Engineering Sample	6.4	1.9	77		
Executives	5.7	2.1	178	**0.35**	**0.34**
Sales Personnel	6.8	1.6	64	**-0.23**	**-0.22**
Employment Counselors	7.5	2.1	36	**-0.55**	**-0.56**
Social Workers	6	1.7	81	**0.22**	**0.22**
Mechanics	4.9	1.2	40	**0.94**	**0.88**
Electricians	3.7	2	67	**1.38**	**1.38**
Scientific Prof	5.6	2.4	144	**0.37**	**0.36**
Privateness (N)					
Engineering Sample	6.8	1.7	77		
Executives	6.2	2.1	178	**0.31**	**0.30**
Sales Personnel	5.2	1.7	64	**0.94**	**0.94**
Employment Couns	4.1	2.1	36	**1.41**	**1.46**
Social Workers	5.7	1.7	81	**0.65**	**0.64**
Mechanics	6.4	1.5	40	**0.25**	**0.24**
Electricians	6.4	2.4	67	**0.19**	**0.19**
Scientific Prof	5.5	1.8	144	**0.74**	**0.73**
Opennes to Change (Q1)					
Engineering Sample	6.6	1.9	77		
Executives	6.4	1.9	178	**0.11**	**0.10**
Sales Personnel	4.6	1.6	64	**1.14**	**1.12**
Employment Couns	5.9	2.1	36	**0.35**	**0.35**
Social Workers	6.2	1.8	81	**0.22**	**0.22**
Mechanics	5.3	0.9	40	**0.87**	**0.79**
Electricians	4.5	2.4	67	**0.97**	**0.97**
Scientific Professions	6.2	1.3	144	**0.25**	**0.26**

16PF _ Continued

16 PF	Mean	Std Dev	Sample Size	Comparison with the engineering sample Cohen's *d*	Hedges $\hat{g}$
Sensitivity (I)					
Engineering Sample	4.4	2	77		
Executives	5.6	2.1	178	**-0.59**	**-0.58**
Sales Personnel	7.3	1.5	64	**-1.64**	**-1.61**
Employment Counselors	8.6	1.7	36	**-2.26**	**-2.18**
Social Workers	7.2	1.6	81	**-1.55**	**-1.54**
Mechanics	5	1.2	40	**-0.36**	**-0.34**
Electricians	3.9	2.2	67	**0.24**	**0.24**
Scientific Professions	7.1	1.8	144	**-1.42**	**-1.44**
Apprehension (O)					
Engineering Sample	5	2.2	77		
Executives	5.5	2	178	**-0.24**	**-0.24**
Sales Personnel	5.8	1.9	64	**-0.39**	**-0.38**
Employment Counselors	6.5	2	36	**-0.71**	**-0.70**
Social Workers	4.7	2.2	81	**0.14**	**0.14**
Mechanics	3.2	1.8	40	**0.90**	**0.86**
Electricians	3.8	2.2	67	**0.55**	**0.54**
Scientific Professions	3.6	2.1	144	**0.65**	**0.65**
Tension (Q4)					
Engineering Sample	4.8	1.7	77		
Executives	5.3	2	178	**-0.27**	**-0.26**
Sales Personnel	5.6	1.6	64	**-0.48**	**-0.48**
Employment Counselors	6.7	1.9	36	**-1.05**	**-1.07**
Social Workers	4.8	1.9	81	**0.00**	**0.00**
Mechanics	5.4	1.5	40	**-0.37**	**-0.36**
Electricians	4.8	1.9	67	**0.00**	**0.00**
Scientific Professions	5.1	1.9	144	**-0.17**	**-0.16**
Warmth (A)					
Engineering Sample	6.6	1.8	77		
Executives	7.8	2.5	178	**-0.55**	**-0.52**
Sales Personnel	5.9	2.3	64	**0.34**	**0.34**
Employment Counselors	7.1	2.4	36	**-0.24**	**-0.25**
Social Workers	8	2.2	81	**-0.70**	**-0.69**
Mechanics	5.5	2.5	40	**0.50**	**0.53**
Electricians	4.6	2.4	67	**0.94**	**0.95**
Scientific Professions	3.4	2	144	**1.68**	**1.65**

APPENDIX C

COMPLEXITY LEVELS CORRESPONDING TO OCCUPATIONS WITHIN HOLLAND'S RI and IR CODES

Cognitive Complexity Levels Corresponding To Occupations Within Holland's RI Code

	Cx	HOC	Title	DOT
High level of complexity	77	RIE	Geologist	024.061-022
	76	RIE	Petroleum Engineer	010.061-018
	75	RIE	Mechanical-Design Engineer	007.061-018
	74	RIE	Mining Engineer	010.061-014
	73	RIS	Mechanical Engineer	007.061-014
	72	RIC	Optical Engineer	019.061-018
	71	RIE	Automotive Engineer	007.061-010
	71	RIE	Electronics Engineer	003.061-030
Moderate level of complexity	70	RIC	Heat-Transfer Technician	007.181-010
	69	RIE	Drafter	019.261-014
	68	RIE	Quality Control Technician	012.261-014
	67	RIS	Nuclear Medicine Technologist	078.361-018
	66	RIC	Civil Engineering Technician	005.261-014
	66	RIE	Electrical Technician	003.161-010
	65	RIE	Automobile Design Drafter	017.281-026
	64	RIE	Electromechanical Technician	710.281-018
	63	RIE	Machine shop Tool-and-Die Marker	601.260-010
	62	RIS	Machine shop Machinist	600.260-022
	61	RIS	Ballistic Laboratory Gunsmith	609.260-010
	60	RIS	Radiation-Therapy Technologist	078.361-034
	59	RIE	Electronics Inspector	726.381-010
	58	RIS	Radiographer	199.361-010
	57	RIE	Electrical and Radio Mock-Up Mechanic	693.381-026
	56	RIS	Construction Carpenter	860.381-042
	55	RIS	Machine Operator	616.360-026
	54	RIA	Lighting-Equipment Operator	962.381-014
	53	RIE	Automobile Body Repairer	807.381-010
Low level of complexity	52	RIE	Chemical Preparer	550.685-030
	51	RIE	Rafter-Cutting-Machine Operator	669.382-014
	50	RIE	Tractor-Trailer-Truck Driver	904.383-010
	49	RIE	Construction Worker	869.664-014
	48	RIE	Farm-Machine Operator	409.683-010
	47	RIS	Operating Engineer	859.683-010
	46	RIE	Agricultural Yard Worker	929.583-010
	45	RIS	Log-Truck Driver	904.683-010
	44	RIE	Painter	749.684-038
	43	RIE	Mill Helper	502.684-014
	42	RIE	Plastics Heat Welder	553.684-010
	41	RIE	Poultry Farm Laborer	411.687-018
	40	RIE	General Laborer	559.685-110

Notes. Cx: Level of Cognitive Complexity, HOC: Holland Occupational Code, DOT: Dictionary of Occupational Titles.

Cognitive Complexity Levels Corresponding to Occupations within Holland's IR Code

	Cx	HOC	Title	DOT
High level of complexity	80	IRE	Astronomer	021.067-010
	80	IRE	Chemical Engineer	008.061-018
	80	IAR	Biologist	041.061-030
	79	IRE	Engineering and Scientist Programmer	030.162-018
	79	IRE	Electrical Power System Engineer	003.167-018
	79	IRE	Nuclear Engineer	015.061-014
	78	IRS	Geneticist	041.061-050
	78	IRS	Medical Physicist	079.021-014
	78	IRS	Engineering	045.061-014
	78	IER	Mathematician	020.067-014
	77	IRS	Geophysicist	024.061-030
	76	IRS	Neurologist	070.101-050
	75	IRE	Software Engineer	030.062-010
	74	IRE	Science and Mathematics Faculty Member	090.227-010
	73	IRE	Civil Engineer	005.061-010
	71	IRS	Structural Engineer	005.061-034
	70	IRE	Mechanical Design Engineer	007.161-022
Moderate level of complexity	69	IRE	Electronics Technician	003.161-014
	68	IRE	Biochemistry Technologist	078.261-014
	67	IRS	Chemical Laboratory Technician	022.261-010
	66	IRE	Mechanical Engineering Technician	007.161-026
	66	IRC	Structural Drafter	005.281-014
	65	IER	Geophysical Prospecting Surveyor	018.167-042
	64	IRE	Civil Drafter	005.281-010
	63	IRE	Photo-Optics Technician	029.280-010
	62	IRS	Scientific Photographer	143.062-026
	61	IRS	Hydrographer	025.264-010
	60	ISR	Cardiopulmonary Technologist	078.362-030
	59	IRS	Network Control Operator	031.262-014
	58	IRE	Medical-Laboratory Technician	078.381-014
	56	ISR	Surgical Technician	079.374-022
	55	IRC	Laboratory Assistant, Culture Media	559.384-010
Low level of complexity	54	IRS	Textile Laboratory Assistant	029.381-014
	53	IRS	Videotape Operator	194.382-018

Notes. Cx: Level of Cognitive Complexity, HOC: Holland Occupational Code, DOT: Dictionary of Occupational Titles. In the Dictionary of Occupational Holland Codes, the High complexity level jobs comprise 61%, Medium-to-High complexity level jobs comprise 34%, Low-to-Medium complexity level jobs comprise 5%, and Low complexity level jobs comprise 0% of the Investigative theme occupations.

APPENDIX D

SKILLS, ABILITIES, AND WORK ACTIVITIES BY OCCUPATIONAL COMPLEXITY LEVEL

LOWER COMPLEXITY JOBS DOT complexity level range: Below 56. Complexity with dealing with Data=3 and above (3 = Compiling, 4 = Computing, 5 = Copying, 6 = Comparing)	Holland codes: RIS, RIE, IRC, IRS Example Occupations: Machine Operator, Auto-Body Repairer, Chemical Preparer, Operating Engineer, Agricultural Yard Worker, Log-Truck Driver, Construction Worker, General Laborer, Laboratory Assistant-Culture Media, Laboratory Assistant-Textile
Skills	**Example Items**
- Equipment Maintenance: Performing routine maintenance on equipment and determining when and what kind of maintenance is needed. - Management of Material Resources: Obtaining and seeing to the appropriate use of equipment, facilities, and materials needed to do certain work. - Operation and Control: Controlling operations of equipments or systems.	
- Operation Monitoring: Watching gauges, dials, or other indicators to make sure a machine is working properly.	Numerical Domain, Comparing e.g. "I would not mind keeping track of displays with numbers (like gauges)." Spatial Domain, Comparing e.g. "I would like keeping track of graphical displays (such as a Global Positioning System used in cars.)"
- Installation: Installing equipment, machines, wiring, or programs to meet specifications.	Spatial Domain, Copying e.g. "I can get frustrated while trying to assemble a 3-D object/system following instructions from the manual."
- Judgment and Decision Making: Considering the relative costs and benefits of potential actions to choose the most appropriate one. - Troubleshooting: Determining causes of operating errors and deciding what to do about it.	Ideas Domain, Compiling e.g. "For the troubleshooting of an equipment or scientific simulation, I would find it annoying to look for relevant ideas in different sources."

LOWER COMPLEXITY JOBS DOT complexity level range: Below 56. Complexity with dealing with Data=3 and above (3 = Compiling, 4 = Computing, 5 = Copying, 6 = Comparing)	Holland codes: RIS, RIE, IRC, IRS Example Occupations: Machine Operator, Auto-Body Repairer, Chemical Preparer, Operating Engineer, Agricultural Yard Worker, Log-Truck Driver, Construction Worker, General Laborer, Laboratory Assistant-Culture Media, Laboratory Assistant-Textile
Abilities	**Example Items**
- Deductive Reasoning: The ability to apply general rules to specific problems to produce answers that make sense.	Numerical Domain, Computing Simple e.g. "I like applying basic arithmetic principles to specific problems." Ideas Domain, Compiling e.g. "In STEM related areas I like learning the basic principles and applying them to specific problems."
- Gross Body Coordination: The ability to coordinate the movement of your arms, legs, and torso together when the whole body is in motion. - Manual Dexterity: The ability to quickly move your hand, together with your arm, or two hands to grasp, manipulate, or assemble objects. - Control Precision: The ability to quickly and repeatedly adjust the controls of a machine or a vehicle to exact positions. - Depth Perception: The ability to judge which of several objects is closer or further away from you, or to judge the distance between you and an object.	

LOWER COMPLEXITY JOBS DOT complexity level range: Below 56. Complexity with dealing with Data=3 and above (3 = Compiling, 4 = Computing, 5 = Copying, 6 = Comparing)	Holland codes: RIS, RIE, IRC, IRS Example Occupations: Machine Operator, Auto-Body Repairer, Chemical Preparer, Operating Engineer, Agricultural Yard Worker, Log-Truck Driver, Construction Worker, General Laborer, Laboratory Assistant-Culture Media, Laboratory Assistant-Textile
Work Activities	**Example Items**
- Operating Vehicles, Mechanized Devices, or Equipment: Running, maneuvering, navigating, or driving vehicles or mechanized equipment, such as forklifts, passenger vehicles, aircraft, or water craft. - Estimating the Quantifiable Characteristics of Products, Events, or Information: **Estimating sizes, distances**, and quantities; or determining time, costs, resources, or materials needed to perform a work activity.	Spatial Domain, Comparing e.g. “I would dislike trying to estimate the sizes and distances of objects.”
- Identifying Objects, Actions, and Events: Identifying information by categorizing, estimating, recognizing differences or similarities, and detecting changes in circumstances or events. - Inspecting Equipment, Structures, or Material: Inspecting equipment, structures, or materials to identify the cause or errors or other problems or defects.	Numerical Domain, Comparing e.g. “I would not mind comparing two sets of numbers such as an income and expenses table.” Symbolic Domain, Comparing e.g., “I don’t mind looking at two formulas and deciding whether they are conceptually identical.”
- Getting Information: Observing, receiving, and otherwise obtaining information from all relevant sources.	Numerical Domain, Compiling e.g., “I would happily look for and compile numerical results on a topic from different sources.” Ideas Domain, Compiling e.g. “I would enjoy going through different sources to search for different perspectives on a STEM related topic.”

MODERATE COMPLEXITY JOBS DOT complexity level range: 56-70. Complexity with dealing with Data=1,2,3 (3 = Compiling, 2 = Analyzing, 1 = Coordinating)	Holland codes: RIE, RIC, RIS, IRE, IRS, IRC Example Occupations: Technicians (e.g., Civil Engineering, Electrical, Electromechanical, Chemical Laboratory, Mechanical Engineering, Photo-Optics, Medical Laboratory, Quality Control), Technologists (e.g., Nuclear Medicine, Radiation-Therapy, Biochemistry), Drafters (e.g., Automobile Design, Structural, Civil), Machine Shop Machinist, Ballistic Laboratory Gunsmith, Electronics Inspector, Radiographer, Geophysical Prospecting Surveyor, Network Control Operator)
Skills	**Example Items**
- Mathematics: Using mathematics to solve problems. - Science: Using scientific rules and methods to solve problems. - Complex Problem Solving: Identifying complex problems and reviewing related information to develop and evaluate options and implement solutions.	Numerical Domain, Computing Levels e.g. "I enjoy working on numerical problems involving exponential numbers," Symbolic Domain, Computing Levels e.g. "I like solving problems using scientific notations and symbols."
- Critical Thinking: Using logic and reasoning to identify the strengths and weaknesses of alternative solutions, conclusions or approaches to problems.	Numerical Domain, Analyzing e.g. "I find it fun to critically evaluate the numerical evidence presented in technical articles or books." Ideas Domain, Analyzing e.g. "I would like to take the responsibility of critically analyzing the strengths and weaknesses of technical propositions in STEM fields."
Abilities	**Example Items**
- Mathematical Reasoning: The ability to choose the right mathematical methods or formulas to solve a problem.	Symbolic Domain, Computing e.g. "I enjoy trying to figure out what mathematical or scientific formulas to use in a problem."
- Visualization: The ability to imagine how something will look after it is moved around or when its parts are moved or rearranged.	Spatial Domain, Computing e.g. "I enjoy imagining how something will look after its parts are rearranged."
- Information Ordering: The ability to arrange things or actions in a certain order or pattern according to a specific rule or set of rules (e.g., patterns of numbers, letters, words, pictures, mathematical operations).	

MODERATE COMPLEXITY JOBS DOT complexity level range: 56-70. Complexity with dealing with Data=1,2,3 (3 = Compiling, 2 = Analyzing, 1 = Coordinating)	Holland codes: RIE, RIC, RIS, IRE, IRS, IRC Example Occupations: Technicians (e.g., Civil Engineering, Electrical, Electromechanical, Chemical Laboratory, Mechanical Engineering, Photo-Optics, Medical Laboratory, Quality Control), Technologists (e.g., Nuclear Medicine, Radiation-Therapy, Biochemistry), Drafters (e.g., Automobile Design, Structural, Civil), Machine Shop Machinist, Ballistic Laboratory Gunsmith, Electronics Inspector, Radiographer, Geophysical Prospecting Surveyor, Scientific Photographer, Network Control Operator)
Work Activities	**Example Items**
- Processing Information: Compiling, coding, categorizing, calculating, tabulating, auditing, or verifying information or data. - Updating and using Relevant Knowledge: Keeping up-to-date technically and applying new knowledge to your job.	Symbolic Domain, Compiling e.g. “I would not mind compiling information that is based on formulas” Ideas Domain, Compiling e.g., “I like to keep up to date with the ideas related to STEM areas.”
- Analyzing Data or Information: Identifying the underlying principles, reasons, or facts of information by breaking down information or data into separate parts. - Monitor Processes, Materials, or Surroundings: Monitoring and reviewing information from materials, events, or the environment, to detect or assess problems.	Numerical Domain, Analyzing e.g. “When reading something technical, I like to analyze the numerical evidence they present to check its accuracy.”
- Repairing and Maintaining Electronic Equipment: Servicing, repairing, calibrating, regulating, fine-tuning, or testing machines, devices, and equipment that operate primarily on the basis of electrical or electronic principles.	

HIGH COMPLEXITY JOBS DOT complexity level range: 70-80. Complexity with dealing with Data=0 (0 = Synthesizing), and the level of Generating, which was added.	Holland codes: RIE, RIC, IRE, IRS, IER Example Occupations: Engineer (e.g., Electronics, Automotive, Optical, Mechanical, Mining, Petroleum, Chemical, Nuclear, Software, Civil, Structural), Scientist (e.g., Astronomer, Biologist, Geologist, Geneticist, Medical Physicist, Geophysicist, Faculty member), Mathematician
Skills	**Example Items**
- Systems analysis: Determining how a system should work and how changes in conditions, operations, and the environment will affect outcomes. - Operations Analysis: Analyzing needs and product requirements to create a design.	Ideas Domain, Synthesizing e.g. "I may hesitate to search interdisciplinary fields to identify product requirements in a STEM related area."
- Technology Design: Generating or adapting equipment and technology to serve user needs.	Symbolic Domain, Generating e.g. "I would enjoy using abstract mathematical and scientific concepts to generate more advanced technologies."
Work Activities	**Example Items**
- Thinking Creatively: Developing, designing, or creating new applications, ideas, relationships, systems, or products.	Spatial Domain, Generating e.g. "I would like to have the responsibility of generating a novel 3-dimensional system with real world applications."
Abilities	**Example Items**
- Originality: The ability to come up with unusual or clever ideas about a given topic or situation, or to develop creative ways to solve a problem.	Symbolic Domain, Generating e.g. "I would be interested in creating a new expression for a technical concept using mathematical or scientific parameters (formulas)."
- Fluency of Ideas: The ability to come up with a number of ideas about a topic.	Ideas Domain, Generating e.g., "I would enjoy spending time on thinking to come up with a number of ideas about a topic related to STEM."
- Inductive Reasoning: The ability to combine pieces of information to form general rules or conclusions (includes finding a relationship among seemingly unrelated events).	Numeric Domain, Synthesizing e.g., "I would like working on problems that necessitate integrating numerical results."

APPENDIX E

STEM INTEREST COMPLEXITY MEASURE EXAMPLE ITEMS

Instructions: The following items include some tasks and activities that individuals may or may not be interested in engaging. Please indicate the degree to which each statement is true of you.

1 = Very untrue of me
2 = Untrue of me
3 = Somewhat untrue of me
4 = Somewhat true of me
5 = True of me
6 = Very true of me

Numeric Scale Example Items
Low complexity: I would not mind keeping track of displays with numbers (like gauges).
Moderate complexity: I find it fun to critically evaluate the numerical evidence presented in technical articles or books.
High complexity: I would like working on problems that necessitate integrating numerical results.

Symbolic Scale Example Items
Low complexity: I won't get frustrated if I need to copy a formula with scientific notations.
Moderate complexity: I do not like solving for equations represented only by symbolic formulas with very few numbers (e.g., $y(t) = 1/\sqrt{2}\int sin \sqrt{2}(t-\tau.)d\tau)$. (R)
High complexity: While thinking about a real world technical problem I would be interested in modeling it with mathematical statements (e.g. formulas).

Spatial Scale Example Items
Low complexity: I would like keeping track of graphical displays (such as a Global Positioning System used in cars).
Moderate complexity: I enjoy trying to solve a spatial geometry problem.
High complexity: I would like to have the responsibility of generating a novel 3-dimensional system with real world applications.

Ideas Scale Example Items
Low complexity: I enjoy comparing and contrasting two perspectives on a topic related to STEM areas.
Moderate complexity: I would like to critically analyze the strengths and weaknesses of technical propositions in STEM fields.
High complexity: I would find it exciting to work on coming up with original ideas in the domain of technological advancements.

Note. * STEM refers to Science, Math, Engineering, and Technology.

Assessing General STEM Interest Complexity

Instructions: Now please rate your degree of interest for the following levels of being involved in math, physical sciences, and technology.

How interested would you be in doing what is conveyed in the following statements?

1 = **Not** interested **at all**
2 = **Not** interested
3 = Somewhat **uninterested**
4 = Somewhat interested
5 = Interested
6 = Very much interested

<u>General Interests Scale Examples</u>
Low complexity: Learning about interesting facts in sciences or technology from magazines or the TV.
Moderate complexity: Learning about the underlying mathematical and scientific principles of new technologies.
High complexity: Taking the challenge of building theories based on your advanced knowledge of mathematics, sciences, and technology.

APPENDIX F

EXAMPLES OF INTERESTS IN GENERAL LEVEL OF INVOLVEMENT WITH STEM

Presented below are tasks and activities related to two areas from the sciences and technology domain (i.e., mechanics and machines, and studying the human anatomy). These activities are ordered in terms of their complexity levels ranging from "getting the general idea" to "formulating ideas." A person may have a general interest towards "studying the human body" nevertheless may not be interested in the higher level activities related to studying the human body. The 15 items assessing the general level of complexity in STEM areas correspond to the identified complexity levels as follows: Items 1, 2, 3 correspond to Level 1; items 4, 5 , 6 correspond to Level 2; items 7, 8 correspond to Level 3; items 9, 10, 11 correspond to Level 4; and items 12, 13, 14, 15 correspond to Level 5.

Complexity Level	Example area of Interest: Mechanics and Machines	Example area of Interest: The human body
1. Getting the general idea, without going into technical jargon and detail.	- Like to learn about the history of developments in mechanics and machines, such as an engine.	- Learning some general facts about the human body from TV documentaries, or anatomy books with general information, such as the general structure and function of our brain.
2. Acquiring more detailed and specialized knowledge, but without learning about the empirical studies that underlie knowledge.	- Like to figure out how a machine works. - Like to understand the math and scientific principles of how a machine works.	- Reading more detailed information about an aspect of the human body from a professional book or scientific review articles.
3. Following the empirical literature in detail.	- Like to follow the scientific literature on mechanics and machines.	- Following the research conducted on a specialized topic by reading empirical articles.
4. Critically evaluating the empirical literature	- Like to analyze the literature and existing systems and focus on areas of improvement.	- Analyzing the debates or controversies in the scientific literature to understand what areas are in need of improvement.
5. Formulating ideas to investigate	- Like to work on improving a mechanical system based on knowledge of principles of math, science, and engineering - Like to design new mechanical systems based on knowledge of math and science. - Like creating new formulations for a mechanical system.	- Devoting time to research by coming up with new hypotheses/ ideas to test that could lead to improvements in the field.

APPENDIX G

INFORMATION ON THE IPIP SCALES AND COGNITIVE ABILITY TESTS

IPIP SCALES

Scale reliabilities and converging validities are provided in the IPIP website (IPIP, 2008) and are reported below.

O5: Intellect. IPIP O5: Intellect was developed to model the Openness to Ideas facet of the broader Big Five Openness to Experience Factor. Items refer to a tendency to think, discuss, and being open to abstract ideas and challenging reading material and complex problem solving. The IPIP scale consists of 10 items. Internal consistency reliability has been reported to be .86. It correlates highly with the Openness to Ideas facet of the NEO-PI-R (r = .80 and r = .95 after correction for unreliability).

Intellect. IPIP Intellect was developed to model the 16PF Reasoning-Factor B. It consists of 13 items, which refer to a tendency to reflect on thoughts and problems, and analyze things. The internal consistency reliability of the scale is reported to be .76. The IPIP Intellect was found to correlate .51 with the 16PF Reasoning-Factor B (r = .69 corrected for scale unreliability).

Creativity. Items from the two IPIP Creativity scales that were developed to model the Hogan Personality Inventory (HPI) Intellectance construct and the AB5C V+/II- facet under the Openness factor will be included in the study. The scale has 12 items referring to a tendency of thinking of new ideas, linking ideas together, and questioning and challenging others' ideas. Internal consistency reliabilities of .81 and .83 have been reported for the entire 10-item scales. The IPIP Creativity scale correlated .64 (r = .81 after correction for scale unreliability) with the HPI Intellectance scale.

Judgment/Open-mindedness. This scale was developed to correspond to the respective facet of the Values in Action Scale (Peterson & Seligman, 2004). It consists of nine items which refer to a tendency of judging the reasons and the pros and cons, and being open to ideas while decision making. An internal consistency reliability of .80 has been reported for the scale.

Planfulness. IPIP Planfulness was developed to correspond to the MPQ Control factor. The scale consists of 10 items which refer to a tendency to think through things and plan accordingly. The internal consistency reliability is .78, correlates with the 1 MPQ Control factor by .70 (r = .87 after correction for scale unreliability).

Dutifulness. IPIP Dutifulness was developed to model the 16PF Rule-Consciousness factor (Factor G). The scale has 10 items which refer to a tendency of following the rules and adhering to authority. The scale has an internal consistency reliability of .84, and correlates with the 16PF Rule-Consciousness factor by .69 (r = .87 after correction for scale unreliability).

Forcefulness. IPIP Forcefulness was developed to model the California Personality Inventory (CPI) Masculinity factor. The scale has 10 items referring to a tendency of taking initiative and overcoming setbacks. The scale has an internal consistency reliability of .82 and it correlated with the CPI Masculinity scale by .73 (r = .86 after correcting for scale unreliability).

Self-sufficiency. IPIP Self-sufficiency was developed to correspond to the Self-reliance facet under the Independence factor of the 6 Factor Personality Questionnaire (6FPQ). The scale has 10 items referring to a tendency to be self-reliant in making decisions and not being worrisome or dependent on others. An internal consistency reliability of .59 was reported. The scale correlates with the 6FPQ Self-reliance facet by .57 (r = .98 corrected for unreliability).

Toughness. IPIP Toughness corresponds to the AB5C IV+/V+ vs IV-/V- facet that correspond to portions of the Big Five Agreeableness factor. The scale has 12 items referring to a tendency to be and remain calm, not get offended or hurt easily, and able to cope with setbacks. The internal consistency reliability was reported to be .84.

Poise. IPIP Poise was developed to model the CPI Tough-mindedness factor. The scale has 10 items which refer to knowing what to do and being calm under pressure. The internal consistency reliability is .79 and it correlates with the CPI Tough-mindedness by .69 (r = .90 after correcting for scale unreliability).

Warmth. IPIP Warmth was developed to model the 16PF Factor A: Warmth. It has 10 items which refer to being concerned about other people. The internal consistency reliability is .80 and it correlates with the 16PF Factor A: Warmth by .64 (r = .84 after correcting for scale unreliability).

Emotionality. IPIP Emotionality was developed to model the NEO-PI O3: Openness to Feelings. It has 10 items referring to being concerned about own and others' feelings. The internal consistency reliability is .81 and it correlates with the 16PF Factor A: Warmth by .70 (r = .90 after correcting for scale unreliability).

Risk-avoidance. IPIP Risk-avoidance was developed to model the MPQ Harm-avoidance. It has 10 items referring to a tendency to avoid physically risky situations. An internal consistency reliability of .80 was reported and it correlates with the MPQ Harm-avoidance scale by .49 (r = .60 after correcting for scale unreliability).

Achievement Striving. The three IPIP Achievement Striving scales were developed to model the NEO Conscientiousness Achievement striving facet, the MPQ Achievement factor, and the 6FPQ IT1: Achievement factor. Each scale has 10 items.

Internal consistency reliabilities were reported as .78, .79, and .82, respectively. NEO Conscientiousness Achievement striving facet, the MPQ Achievement factor, and the 6FPQ Achievement factor correlated by .70 .64, and .53 with their respective IPIP scales (correlations were .97, .79, and .85, after correcting for scale unreliability).

Planfulness. One of the IPIP Planfulness scales was developed to model the CPI Achievement-via-Conformance factor. The scale has 10 items referring to making an effort to follow one's commitments. The internal consistency reliability was reported to be .62, and a correlation of .53 with the CPI Achievement-via-Conformance factor (r = .81, after correcting for scale unreliability).

The above scales have some overlapping content with the same items. The overlapping items were dropped. Furthermore, items that has a very similar counterpart in terms of content (e.g., "have a good imagination" and "do not have a good imagination") were dropped. Finally, items were dropped if they did not appear to be face valid with the construct under focus (e.g., "try to avoid complex people" as a Creativity item) or they were ambiguous (e.g., "do things men traditionally do"). As a result, a total of 125 items are included to assess the personality of engineers and scientists.

BIG FIVE IPIP SCALES

Agreeableness. The 10-item IPIP scale has an internal consistency reliability of .77 and it correlates with NEO-PI-R Agreeableness factor by .70 (.85 correcting for scale unreliability).

Conscientiousness. The 10-item scale has an internal consistency reliability of .81 and it correlates with NEO-PI-R Conscientiousness factor by .79 (.92 correcting for scale unreliability).

Extraversion. The 10-item IPIP scale has an internal consistency reliability of .86 and it correlates with NEO-PI-R Extraversion factor by .77 (.88 after correcting for scale unreliability).

Neuroticism. The 10-item IPIP scale has an internal consistency reliability of .86 and it correlates with NEO-PI-R Neuroticism factor by .82 (.92 after correcting for scale unreliability).

Openness to Experience. The 10-item scale has an internal consistency reliability of .82 and it correlates with NEO-PI-R Openness factor by .79 (.91 correcting for scale unreliability).

COGNITIVE ABILITY TESTS INCLUDED IN THE PRESENT STUDY FROM THE ETS KIT (Ekstrom, French, Harman, & Dermen, 1976)

Numerical/Math Reasoning Tests

Arithmetic Aptitude Test: The participant is instructed to solve arithmetic problems by choosing the correct answer out of 5 alternative choices. The test has two parts, each with 15 problems and 10 minutes for completion. An alternate form reliability of .83 has been reported with a sample of 12th graders. Only one part will be administered to the participants.

Mathematic Aptitude Test: The participants are presented with word problems to solve and instructed to choose the correct answer out of 5 alternative choices. The problems require arithmetic or very simple algebraic concepts. The test is related to the ability to select and organize relevant information for the solution of a problem, using numerical information. The test has two parts, each with 15 problems and 10 minutes for completion. An alternate form reliability of .81 has been reported with a sample of army enlistees. Only one part will be administered to the participants.

Necessary Arithmetic Operations Test: The participants are instructed to determine what numerical operations are required to solve arithmetic problems without actually having to carry out the computations. The test is related to the ability to select and organize relevant information for the solution of a problem, using numerical information. The test has two parts, each with 15 items and 5 minutes for completion. An alternate form reliability of .73 has been reported with a sample of college males. Only one part will be administered to the participants.

Arithmetic aptitude, Mathematic aptitude, and Necessary arithmetic operations all load under the General Reasoning factor in the ETS Kit. (Ekstrom et al.,1976). The General Reasoning factor was shown to be loading under a Quantitative factor, together with ASVAB Math knowledge and Arithmetic reasoning factors (Roberts, Goff, Anjoul, Kyllonen, Pallier, & Stankov, 2000).

Verbal Ability Tests

Controlled Associations Test: The participant is instructed to write as many synonyms as possible (up to 12) for each word presented. The test is related to associational fluency that is the ability to rapidly produce words which share a given semantic property. The test has two parts, each with 4 given words and 6 minutes for completion. An alternate form reliability of .83 has been reported with a sample of Naval Recruits. Both parts will be administered.

Making Sentences Test: The participant is instructed to make sentences of a specified by presenting the initial letter of some of the words in the sentence. The test is associated with expressional fluency that is producing connected discourse that fits restrictions imposed such as letters, words. The test has two parts, each with 10 items and 5 minutes for completion.

An example is: E _______ *______ R______ T______ *______. A sentence that fits this pattern could be: EVERY *BOY READS THE *BOOK. An alternate form reliability of .80 has been reported with a sample of Naval Recruits. Both parts will be administered to the participants.

Extended Range Vocabulary Test: Participants are presented a word and instructed to choose the word closest in meaning from among five options. The test is related to English verbal comprehension. The test has two parts, each with 24 items and 6 minutes for completion. The items range from very easy to very difficult. An alternate form reliability of .89 has been reported with a sample of army enlistees. Both parts will be administered to the participants.

The three tests appear under the Associational Fluency, Expressional Fluency, and Verbal Comprehension factors of the ETS Kit, respectively. In a sample of airmen (Wothke et al., 1990) the Associational and Expressional fluency factors all loaded under a general Verbal Fluency factor. Verbal Comprehension factors which include vocabulary tests loaded under the general Verbal Memory factor.

Spatial Ability Tests

Cube Comparisons Test: In this test, each item is presented as two drawings of a cube (either the same cube or different cubes). Each side of the cubes has a letter and it is assumed that no cube can have two faces alike. The participants are instructed to indicate whether the two cube drawings can belong to the same cube or not. The test is related to spatial orientation that is the ability to perceive spatial patterns or to maintain orientation with respect to objects in space. The test has two parts, each with 21 items and 3 minutes for completion. An alternate form reliability of .84 has been reported with a sample of college students. Both parts will be administered to the participants.

Paper Folding Test: Each item is presented as successive drawings that illustrate two or three folds made in a square sheet of paper, where the final drawing of the folded paper shows where a hole is punched in it. The participants are instructed to select one of five drawings to show how the punched sheet would appear when fully reopened. The test is related to visualization that is the ability to manipulate or transform the image of spatial patterns into other arrangements. The test has two parts, each with 10 items and 3 minutes for completion. An alternate form reliability of .84 has been reported with samples of college students and army enlistees. Both parts will be administered to the participants.

Surface Development Test: Each item is presented as a drawing of a solid three dimensional form that could be made with paper or sheet metal. With each drawing there is a diagram showing how a piece of paper might be cut and folded so as to make the solid form, where dotted lines show where the paper is folded. One part of the diagram is marked to correspond to a marked surface in the drawing. The participants are instructed to indicate which lettered edges in the drawing correspond to numbered edges or dotted lines in the diagram. The test is related to visualization that is the ability to manipulate or transform the image of spatial patterns into other arrangements. The test has two parts, each with 6 drawings (and 5 numbered edges) and 6 minutes for completion. Alternate form reliabilities around .91 have been reported with samples of college students and army enlistees. Both parts will be administered.

In the ETS Kit, the Cube Comparisons Test is under the Spatial Orientation factor, and the other two tests are under the Visualization factor. Nevertheless, all three tests loaded under a general Spatial Orientation factor (Wothke et al., 1990).

APPENDIX H

MEASURING INTENTIONS TO PERSIST IN AND FURTHER PURSUE STEM AREAS

Intentions to Persist in and Further Pursue STEM Areas

1 = **Very untrue** of me
2 = **Untrue** of me
3 = Somewhat **untrue** of me
4 = Somewhat true of me
5 = True of me
6 = Very true me

Short-term commitment

1. Next semester I intend to continue taking courses related to engineering, sciences, or mathematics.
2. I intend to take courses related to engineering, sciences, or mathematics the following year.
3. I intend to stay in a major related to engineering, sciences, or mathematics.
4. I intend to get a Bachelors degree form a major related to engineering, sciences, or mathematics.

Degree attainment intentions

1. I am planning to apply for a master's education in a field related to engineering, sciences, or mathematics.
2. I intend to get a masters degree in a field related to engineering, sciences, or mathematics.
3. I would like to pursue a PhD in engineering, sciences, or mathematics related area.
4. I am sure that I would like to continue with my education in engineering, sciences, or mathematics.

Long-term commitment

1. I intent to find a job as an engineer, scientist, or mathematician.
2. I can see myself working as an engineer, scientist, or mathematician in the future.
3. I am planning on earning my life as an engineer, scientist, or mathematician.
4. I intend to devote my career to an area related to engineering, sciences, or mathematics.

APPENDIX I

ASSESSING VERTICAL CAREER INTENTIONS

(INTENDED OCCUPATIONAL LEVEL)

Vertical Career Intentions Form

Instructions: Below you will find three cluster of occupations (Identified as Cluster 1, Cluster 2, and Cluster 3). Each cluster is defined by some example occupations, the work activities commonly carried out in such occupations, and the skills and abilities required by the occupations. After reading each cluster, please indicate whether you would like to work in one of the occupations in this cluster or a similar occupation with similar work activities and required skills and abilities (assume that each cluster has the same pay and prestige).

Cluster 1:

Example Occupations: Radiation Therapy Technologist, Electronics Inspector, Medical Laboratory Technician, Radiographer, Machine Operator, Laboratory Assistant

Description of occupations:

Work Activities

- Monitoring and reviewing information from technological equipment, detecting and assessing problems.
- Servicing, repairing, calibrating, regulating, fine-tuning, or testing machines and equipment that operate primarily on the basis of electrical or electronic principles.
- Analyzing work related information to identify the underlying principles, reasons, or facts of information.
- Keeping up-to-date technically and applying new knowledge to your job.

Skills

- Mathematics: Using mathematics to solve work related problems.
- Science: Using scientific rules and methods to solve work related problems.
- Critical Thinking (Using logic and reasoning to identify the strengths and weaknesses of alternative solutions, conclusions or approaches to work related problems.)

Abilities

- Inductive Reasoning (Combining job relevant pieces of information to form relationships or conclusions)
- Oral expression of job related information and ideas.
- Written expression of job related information and ideas.
- Reading Comprehension of work related documents.

How demanding are these occupations in terms of the level of cognitive effort required?

1 = Very undemanding
2 = Undemanding
3 = Somewhat undemanding
4 = Somewhat demanding
5 = Demanding
6 = Very demanding

Would you like to work in one of the occupations in this cluster or a similar occupation with similar work activities and required skills and abilities?

Yes ☐
No ☐

Cluster 2:
Example Occupations:
Engineering and Scientist Programmer, Mechanical Design Engineer, Mechanical Engineering Technician, Electrical or Electronics Technician, Heat-Transfer Technician, Geophysical Prospecting Surveyor, Quality Control Technician, Drafter, Civil Engineering Technician, Electromechanical Technician, Automobile Design Drafter, Biochemistry Technologist, Chemical Laboratory Technician, Structural Drafter, Civil Drafter, Photo-Optics Technician, Hydrographer, Machine Shop machinist, Ballistic Laboratory Gunsmith, Network Control Operator

Description of occupations:
Work Activities
The work activities involved are similar to those of occupations in Cluster 1.
Skills and Abilities
The skills involved in occupations in Cluster 2 include those identified in Cluster 1. In addition, performing occupations in Cluster 2 require "complex problem solving skills" and "mathematical reasoning abilities", as defined below:
- Identifying complex problems and reviewing related information to develop and evaluate options and implement solutions.
- The ability to choose and apply the right mathematical and scientific methods or formulas to solve a problem.

How demanding are these occupations in terms of the level of cognitive effort required?

1 = Very undemanding
2 = Undemanding
3 = Somewhat undemanding
4 = Somewhat demanding
5 = Demanding
6 = Very demanding

Would you like to work in one of the occupations in this cluster or a similar occupation with similar work activities and required skills and abilities?
Yes ☐
No ☐

Cluster 3:

Example Occupations:

Engineering related: Electrical and Electronics Engineer, Industrial Engineering, Mechanical Engineer, Civil Engineer, Structural Engineer, Petroleum Engineer, Mining Engineer, Automotive Engineer, Optical Engineer, Chemical Engineer, Nuclear Engineer, Software Engineer, A faculty position as an engineer

Science related: Geologist, Biologist, Chemist, Astronomer, Physicist, Geneticist, Medical Physicist, Geophysicist, Mathematician, a faculty position as a scientist or mathematician

Description of occupations:

Work Activities

The work activities involved are similar to those of occupations in Cluster2. In addition, performing in Cluster 3 occupations (e.g., engineers, scientists) involves thinking creatively.

- Thinking Creatively: Developing, designing, or creating new applications, ideas, relationships, systems, or products.

Skills and Abilities

The skills involved in occupations in Cluster 3 include those identified in Cluster 1 and 2. In addition, performing occupations in Cluster 3 (e.g. engineering, scientists) require skills related to designing and analyzing technological systems, and abilities related to being original in the work related field and coming up with novel ideas, as defined below:

- Technology Design: Generating or adapting equipment and technology to serve user needs.
- Systems analysis: Determining how a system should work and how changes in conditions, operations, and the environment will affect outcomes.
- Operations Analysis: Analyzing needs and product requirements to create a design.
- Originality: The ability to come up with unusual or clever ideas about a given topic or situation, or to develop creative ways to solve a problem.
- Fluency of Ideas: The ability to come up with a number of ideas about a topic.

How demanding are these occupations in terms of the level of cognitive effort required?

1 = Very undemanding
2 = Undemanding
3 = Somewhat undemanding
4 = Somewhat demanding
5 = Demanding
6 = Very demanding

Would you like to work in one of these occupations in this cluster or a similar occupation with similar work activities and required skills and abilities?

Yes ☐
No ☐

APPENDIX J

SUPPLEMENTARY TABLES FOR RESULTS OBTAINED IN STUDY I AND STUDY II

Table J.1 Cognitive Ability Test Intercorrelations

	1	2	3	4	5	6	7	8	9
1. Arithmetic Aptitude	1.00								
2. Mathematic Aptitude	.61**	1.00							
3. Necessary Arithmetic Operations	.46**	.48**	1.00						
4. Controlled Associations	.14	.21**	.23**	1.00					
5. Sentence Construction	.14	.26**	.20**	.32**	1.00				
6. Extended Range Vocabulary	.14	.20**	.36**	.37**	.24**	1.00			
7. Cube Comparisons	.14	.18**	.11	.12	.14	.03	1.00		
8. Paper Folding	.31**	.27**	.28**	.06	.03	.10	.47**	1.00	
9. Surface Development	.21**	.17*	.17*	.11	.04	.00	.51**	.46**	1.00

Notes. $N = 185$. * $p < .05$; ** $p < .01$.

Table J.2 Intercorrelations between Ability, Vocational Interest, Self-concept, and the Big Five Personality Variables

Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
1. SAT Verbal	1.00																			
2. SAT Math	.29	1.00																		
3. ETS Math	.24	.50	1.00																	
4. ETS Verbal	.42	.07	.34	1.00																
5. ETS Spatial	-.14	.24	.31	.12	1.00															
6. R	-.05	.15	-.02	.00	.21	1.00														
7. I	.09	.03	-.03	.09	.11	.50	1.00													
8. A	.07	-.15	-.16	.13	-.03	.32	.28	1.00												
9. S	.03	-.10	-.07	.06	-.10	.36	.37	.53	1.00											
10. E	-.01	-.13	-.11	-.10	-.23	.17	.12	.24	.60	1.00										
11. C	-.08	.17	.15	-.05	.00	.35	.16	-.09	.20	.56	1.00									
12. Math SC	-.01	.44	.32	.02	.24	.23	.16	-.17	.05	.03	.25	1.00								
13. Science SC	.10	.26	.20	.08	.17	.35	.50	-.03	.20	.10	.14	.63	1.00							
14. Spatial SC	-.12	.16	.04	.05	.34	.49	.25	.18	.21	.04	.07	.46	.50	1.00						
15. Verbal SC	.39	-.15	.06	.38	-.05	.01	.21	.33	.36	.24	-.06	.03	.21	.25	1.00					
16.Big Five: O	.21	-.06	-.20	.06	-.04	.17	.29	.55	.32	.08	-.17	-.11	.10	.25	.38	1.00				
17.Big Five: C	-.03	-.12	-.06	.17	-.07	.15	.18	.02	.26	.18	.19	.12	.20	.13	.16	-.03	1.00			
18.Big Five: N	-.06	-.10	-.09	-.07	.07	-.09	.00	.06	-.15	-.10	-.08	-.25	-.18	-.13	-.15	.03	-.33	1.00		
19.Big Five: E	.03	-.06	-.08	-.04	-.21	-.02	.05	.20	.49	.38	.01	-.01	.09	.08	.20	.19	.29	-.39	1.00	
20.Big Five: A	.08	-.09	-.08	.13	-.02	.18	.21	.20	.28	.12	.10	.02	.05	.10	.06	.06	.41	-.37	.20	1.00

Notes. N = 274, except for the following correlations; N = 212 for SAT Verbal and non-ability variables; N = 220 for SAT Math and non-ability variables, N = 185 for the ETS Kit abilities and non-ability variables; N = 146 for SAT Verbal and ETS Kit abilities; N = 150 for SAT Math and ETS Kit abilities. R: Realistic interests; I: Investigative interests; A: Artistic interests; S: Social interests; E: Enterprising interests; C: Conventional interests; SC: self-concet measure; O: Openness to Experience; C: Conscientiousness; N: Neuroticism; E: Extraversion; A: Agreeableness; ETS: Educational Testing Service. Correlations larger than .15 are significant at alpha .05 and correlations larger than .18 are significant at alpha .01.

Table J.3 Study 1 Intercorrelations between Vocational Criteria

	1	2	3	4	5	6	7	8	9	10	11	12
1. GPA	1.000											
2. STEM GPA	.901**	1.000										
3. STEM Membership	.080	.240**	1.000									
4. STEM BS Intent	.352**	.337**	a	1.000								
5. STEM Grad Intent	.281**	.267**	a	.393**	1.000							
6. STEM Career Intent	.246**	.242**	a	.564**	.567**	1.000						
7. # of HS Math Courses	.144	.179*	.091	.068	.023	.052	1.000					
8. # of HS Science Cours	.047	.066	.228**	.088	.170*	.115	.254**	1.000				
9. HS STEM Competition	.055	.086	.200**	.113	.137	.145*	.107	.162**	1.000			
10. HS STEM Club Part	.067	.112	.247**	.036	.201**	.232**	.168**	.269**	.421**	1.000		
11. College STEM Activity	.048	.001	.154*	.084	.122	.126	.029	.083	.280**	.276**	1.000	
12. Age first wanted STEM	-.056	-.124	-.077	-.123	-.100	-.127	-.101	-.218**	-.238**	-.186**	-.087	1.000

Notes. (a) Correlation cannot be computed as only STEM members responded to intentions to further pursue a STEM field. GPA: Grade Point Average; STEM: Science, Technology, Engineering, and Mathematics; BS: Bachelor of Science; Grad: Graduate; HS: High School; Part: Participation. *$p < .05$; ** $p < .01$.

Table J.4 Study 2 Descriptives for STEM Interest Complexity: All Complexity Levels

Scale (# of items)	Mean	Hedges' $\hat{g}$ Stem$^{(1)}$ *vs* Other$^{(2,3)}$	Sd	Range	Skewness	Cronbach's α
Numeric Low (5)						
STEM[1]	4.05		0.87	5.00	-0.79	0.79
Non-STEM[2]	3.19	0.86$^{(1,2)}$	0.91	4.40	-0.02	0.71
Transfer[3]	3.66	0.44$^{(1,3)}$	1.03	4.20	-0.28	0.79
All sample	3.85		0.96	5.00	-0.53	0.80
Numeric Mod (12)						
STEM[1]	3.75		0.78	4.92	-0.73	0.88
Non-STEM[2]	2.94	1.00$^{(1,2)}$	0.89	4.25	0.21	0.87
Transfer[3]	3.16	0.74$^{(1,3)}$	0.96	3.50	-0.18	0.86
All sample	3.52		0.89	4.92	-0.48	0.89
Numeric High (5)						
STEM[1]	3.73		0.88	5.00	-0.49	0.80
Non-STEM[2]	2.77	1.06$^{(1,2)}$	0.99	4.00	0.18	0.79
Transfer[3]	2.87	0.95$^{(1,3)}$	1.05	3.80	0.01	0.83
All sample	3.44		1.02	5.00	-0.38	0.83
Symbolic Low (4)						
STEM[1]	3.92		0.84	4.75	-0.66	0.69
Non-STEM[2]	2.98	1.12$^{(1,2)}$	0.87	4.00	0.18	0.45
Transfer[3]	3.39	0.50$^{(1,3)}$	1.10	4.50	-0.46	0.77
All sample	3.67		0.96	4.75	-0.49	0.71
Symbolic Mod (16)						
STEM[1]	3.61		0.91	4.38	-0.53	0.94
Non-STEM[2]	2.51	1.25$^{(1,2)}$	0.78	3.63	0.35	0.90
Transfer[3]	2.86	0.81$^{(1,3)}$	1.01	4.00	0.29	0.94
All sample	3.31		1.01	4.38	-0.22	0.95
Symbolic High (8)						
STEM[1]	3.71		0.96	4.88	-0.51	0.90
Non-STEM[2]	2.51	1.27$^{(1,2)}$	0.94	4.00	0.41	0.88
Transfer[3]	3.04	0.69$^{(1,3)}$	1.09	4.38	0.22	0.90
All sample	3.39		1.09	4.88	-0.27	0.92
Spatial Low (6)						
STEM[1]	3.89		0.71	4.00	0.04	0.57
Non-STEM[2]	3.51	0.53$^{(1,2)}$	0.82	3.67	0.07	0.61
Transfer[3]	3.76	0.15$^{(1,3)}$	0.91	4.33	-0.91	0.76
All sample	3.80		0.77	4.67	-0.17	0.61
Spatial Mod (8)						
STEM[1]	3.67		0.92	4.63	-0.51	0.88
Non-STEM[2]	2.77	0.97$^{(1,2)}$	0.96	4.00	0.25	0.86
Transfer[3]	2.96	0.75$^{(1,3)}$	1.05	4.13	0.13	0.87
All sample	3.41		1.02	4.63	-0.32	0.89
Spatial High (7)						
STEM[1]	3.62		1.09	5.00	-0.28	0.92
Non-STEM[2]	2.70	0.85$^{(1,2)}$	1.09	4.29	0.42	0.88
Transfer[3]	2.91	0.65$^{(1,3)}$	1.13	3.71	-0.31	0.89
All sample	3.35		1.17	5.00	-0.15	0.92

Table J.4 (continued).

Scale (# of items)	Mean	Hedges' $\hat{g}$ Stem[(1)] *vs* Other[(2,3)]	Sd	Range	Skewness	Cronbach's α
Ideas Low (2)						
STEM[1]	4.12		0.83	4.00	-0.21	0.49
Non-STEM[2]	3.12	0.89[(1,2)]	1.21	4.50	-0.28	0.64
Transfer[3]	3.57	0.63[(1,3)]	1.12	4.50	0.02	0.43
All sample	3.85		1.04	5.00	-0.60	0.61
Ideas Mod (11)						
STEM[1]	4.09		0.72	4.18	-0.30	0.89
Non-STEM[2]	2.87	1.25[(1,2)]	1.04	4.09	-0.01	0.94
Transfer[3]	3.43	0.65[(1,3)]	1.08	4.09	0.19	0.93
All sample	3.76		0.97	4.91	-0.62	0.94
Ideas High (15)						
STEM[1]	4.25		0.73	3.75	-0.28	0.93
Non-STEM[2]	3.05	1.22[(1,2)]	1.05	4.13	-0.14	0.95
Transfer[3]	3.53	0.65[(1,3)]	1.14	3.67	-0.02	0.96
All sample	3.92		0.99	5.00	-0.65	0.95
General Low (3)						
STEM[1]	4.42		0.84	4.00	-0.30	0.77
Non-STEM[2]	3.55	0.79[(1,2)]	1.16	5.00	-0.08	0.76
Transfer[3]	4.02	0.32[(1,3)]	1.27	5.00	-0.75	0.80
All sample	4.19		1.03	5.00	-0.60	0.80
General Mod (8)						
STEM[1]	4.03		0.86	4.88	-0.61	0.90
Non-STEM[2]	2.86	1.16[(1,2)]	1.05	4.00	0.02	0.91
Transfer[3]	3.38	0.55[(1,3)]	1.22	4.38	-0.31	0.94
All sample	3.72		1.07	4.88	-0.58	0.93
General High (4)						
STEM[1]	4.09		1.00	5.00	-0.59	0.86
Non-STEM[2]	2.78	1.09[(1,2)]	1.25	4.25	0.11	0.89
Transfer[3]	3.21	0.64[(1,3)]	1.41	5.00	-0.11	0.94
All sample	3.72		1.23	5.00	-0.55	0.91

Notes. Variables with an asteriks (*) are formed using unit-weighted z-scores and the composite has been re-standardized. STEM sample N = 274, Non-STEM sample N = 86, transferred from STEM to Non-STEM sample N = 35, all sample N = 398 (three participants did not indicate their major). Mean differences between STEM and non-STEM groups and between STEM and the transfer groups are significant at the .01 level. Differences between the non-STEM and the transfer groups are only significant at the alpha .05 level for the Symbolic, Ideas, General scales, and the composite scale. Hedges' $\hat{g}$ indicates the effect size of the mean differences between STEM and non-STEM (1,2), and between STEM and the transfer groups (1,3). Standard error of skewness for the samples are 0.15 for STEM, 0.26 for non-STEM, 0.40 for transfer, and 0.12 for the entire sample.

Table J.5.1 Dominance Analyses for the STEM GPA Criterion

Subset model (**X**)	$\rho^2_{Y.X}$	Additional Contribution of: X1 (R+I Interest)	X2 (Self-concept)	X3 (STEM Complexity)
Null & k = 0 avr		**0.000**	**0.034**	**0.078**
X_1 (R+I Interest)	0.000		0.034	0.087
X_2 (Self-concept)	0.034	0.000		0.046
X_3 (STEM Complexity)	0.078	0.009	0.002	
k=1 average		**0.004**	**0.018**	**0.066**
X_1X_2	0.034			0.056
X_1X_3	0.087		0.003	
X_2X_3	0.080	0.010		
k=2 average		**0.010**	**0.003**	**0.056**
$X_1X_2X_3$	0.090			
Overall average		**0.005**	**0.018**	**0.067**

Table J.5.2 Dominance Analyses for the Intentions to Pursue a STEM BS Criterion

Subset model (**X**)	$\rho^2_{Y.X}$	Additional Contribution of: X1 (R+I Interest)	X2 (Self-concept)	X3 (STEM Complexity)
Null & k = 0 avr		**0.036**	**0.064**	**0.098**
X_1 (R+I Interest)	0.036		0.048	0.068
X_2 (Self-concept)	0.064	0.020		0.046
X_3 (STEM Complexity)	0.098	0.006	0.012	
k=1 average		**0.013**	**0.030**	**0.057**
X_1X_2	0.084			0.032
X_1X_3	0.104		0.012	
X_2X_3	0.110	0.006		
k=2 average		**0.006**	**0.012**	**0.032**
$X_1X_2X_3$	0.116			
Overall average		**0.018**	**0.035**	**0.062**

Table J.5.3 Dominance Analyses for the Intentions to Pursue a STEM Graduate Degree Criterion

		Additional Contribution of:		
Subset model (**X**)	$\rho^2_{Y.X}$	X1 (R+I Interest)	X2 (Self-concept)	X3 (STEM Complexity)
Null & k = 0 avr		**0.035**	**0.015**	**0.037**
X_1 (R+I Interest)	0.035		0.008	0.017
X_2 (Self-concept)	0.015	0.028		0.023
X_3 (STEM Complexity)	0.037	0.015	0.001	
k=1 average		**0.022**	**0.005**	**0.020**
X_1X_2	0.043			0.010
X_1X_3	0.052		0.001	
X_2X_3	0.038	0.015		
k=2 average		**0.015**	**0.001**	**0.010**
$X_1X_2X_3$	0.053			
Overall average		**0.024**	**0.007**	**0.020**

Table J.5.4 Dominance Analyses for the Intentions to Pursue a STEM Career Criterion

		Additional Contribution of:		
Subset model (**X**)	$\rho^2_{Y.X}$	X1 (R+I Interest)	X2 (Self-concept)	X3 (STEM Complexity)
Null & k = 0 avr		**0.037**	**0.050**	**0.154**
X_1 (R+I Interest)	0.037		0.036	0.119
X_2 (Self-concept)	0.050	0.023		0.105
X_3 (STEM Complexity)	0.154	0.002	0.001	
k=1 average		**0.013**	**0.019**	**0.112**
X_1X_2	0.073			0.084
X_1X_3	0.156		0.001	
X_2X_3	0.155	0.002		
k=2 average		**0.002**	**0.001**	**0.084**
$X_1X_2X_3$	0.157			
Overall average		**0.017**	**0.023**	**0.117**

Table J.5.5 Dominance Analyses for the Major Satisfaction Criterion

Subset model (**X**)	$\rho^2_{Y.X}$	Additional Contribution of: X1 (R+I Interest)	X2 (Self-concept)	X3 (STEM Complexity)
Null & k = 0 avr		**0.020**	**0.110**	**0.124**
X_1 (R+I Interest)	0.020		0.096	0.104
X_2 (Self-concept)	0.110	0.006		0.046
X_3 (STEM Complexity)	0.124	0.000	0.032	
k=1 average		**0.003**	**0.064**	**0.075**
X_1X_2	0.116			0.040
X_1X_3	0.124		0.032	
X_2X_3	0.156	0.000		
k=2 average		**0.000**	**0.032**	**0.040**
$X_1X_2X_3$	0.156			
Overall average		**0.008**	**0.069**	**0.080**

Table J.5.6 Dominance Analyses for the Academic Adjustment Criterion

Subset model (**X**)	$\rho^2_{Y.X}$	Additional Contribution of: X1 (R+I Interest)	X2 (Self-concept)	X3 (STEM Complexity)
Null & k = 0 avr		**0.002**	**0.104**	**0.083**
X_1 (R+I Interest)	0.002		0.102	0.086
X_2 (Self-concept)	0.104	0.000		0.021
X_3 (STEM Complexity)	0.083	0.005	0.042	
k=1 average		**0.003**	**0.072**	**0.054**
X_1X_2	0.104			0.026
X_1X_3	0.088		0.042	
X_2X_3	0.125	0.005		
k=2 average		**0.005**	**0.042**	**0.026**
$X_1X_2X_3$	0.130			
Overall average		**0.003**	**0.073**	**0.054**

Table J.5.7 Dominance Analyses for the Vertical Career Intentions (Occupational Level) Criterion

		Additional Contribution of:		
Subset model (**X**)	$\rho^2_{Y.X}$	X1 (R+I Interest)	X2 (Self-concept)	X3 (STEM Complexity)
Null & k = 0 avr		**0.031**	**0.047**	**0.107**
X_1 (R+I Interest)	0.031		0.035	0.079
X_2 (Self-concept)	0.047	0.019		0.064
X_3 (STEM Complexity)	0.107	0.003	0.004	
k=1 average		**0.011**	**0.020**	**0.072**
X_1X_2	0.066			0.048
X_1X_3	0.110		0.004	
X_2X_3	0.111	0.003		
k=2 average		**0.003**	**0.004**	**0.048**
$X_1X_2X_3$	0.114			
Overall average		**0.015**	**0.024**	**0.076**

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Vita

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