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The Relation of Scientific Attitudes to Traits, Abilities, and Interests

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ABSTRACT

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Investigating differences between scientists and other chosen occupations dates back to Galton's (1887) study on scientific eminence. However, many of the available assessments for investigating differences in scientific attitudes have failed to incorporate literature on individual differences and have not survived psychometric evaluation. The result is that incorporating scientific attitudes into differential psychology remains a challenge and continues to be a barrier in collaboration between qualitative and quantitative disciplines.

The purpose of this research was to propose and validate a framework for assessing and understanding individual differences in attitudes about science. In addition to developing and validating a revised assessment of scientific attitudes, this work incorporates research on personality traits, cognitive ability, and motivational interests (i.e., TAI) in order to provide integration with various approaches in differential psychology. The result is a framework for assessing scientific attitudes that can enable collaboration between education sciences, cognitive psychologists, and differential psychologists and additionally serve as a basis for further

research on the role of traits, abilities, and interests in developing and predicting interest in science.

In Chapter 2, we examined the psychometric properties of the SAI-II using factor analysis and item response theory. Study 1 (N $= 301$, 134 men) supported a 4-factor structure in which many items had good discrimination and high item information values. The proposed measure of scientific attitudes, the SAI-III, was derived from iterative factor analyses in Chapter 2 conducted on items from the SAI-II and can be scored as 4 separate scales. It is argued that the SAI-III scales can be integrated into existing constructs of personality, ability, and interests and provide incremental information over the existing constructs. Study 2 (N $= 2,324$, 808 men) replicated the structure of Study 1 and examined its structural validity using a diverse online sample. Our results suggest interpreting scientific attitudes as a multidimensional construct using the scales of *Interest in Science*, *Understanding of Science*, *Science Leads to Answers*, and *Openness to Science*. In Chapter 3, concurrent and convergent validity of the proposed SAI-III scales was established using assessments for personality traits, cognitive ability, and vocational interests. Meaningful correlations were found for Openness-Intellect as well as all domains of cognitive ability as measured by the International Cognitive Ability Resource. Chapter 4 then concludes by using a large national sample collected by Project TALENT to examine associations of temperament, ability, and interests with scientific attitudes as measured by the Project TALENT INVENTORY. Results partially replicate the patterns of associations of ability and temperament between the SAI-III and measures of TAI, although the magnitudes of the patterns differ between samples. Differences between samples could indicate that temperament guides interest in science throughout high school, whereas ability plays a larger role in adulthood. Taken together, this work proposes a framework for understanding scientific attitudes embedded in differential psychology and provides a public-domain measure of assessing scientific attitudes that can serve as an initial framework across disciplines of education science and psychology.

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It is arguable that good science requires the collaboration of many people with different skill sets and domains of expertise. This dissertation is no exception. Over the past years, only the immense support from multiple individuals has made this possible.

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I also thank David Uttal for his collaboration over many years with our work evaluating children's grasping errors and Dan Mroczek for his patience with me throughout my time in graduate school.

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Jason Allen French

Dedication

To my grandmother and my late grandfather.

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CHAPTER 1

Individual Differences in Scientific Attitudes

> "The phrase "nature and nurture" is a convenient jingle of words, for it separates under two distinct heads the innumerable elements of which personality is composed. Nature is all that man brings with himself into the world; nurture is every influence from without that affects him after his birth. The distinction is clear: that one produces the infant such as it actually is, including its latent faculties of growth of body and mind; the other affords the environment amid which the growth takes place, by which natural tendencies may be strengthened or thwarted, or wholly new ones implanted."
>
> *Sir Francis Galton, 1874, p. 9*

Scientific attitudes are emotional feelings and intellectual beliefs that describe one's positive or negative positions toward different facets of science (Moore & Foy, 1997). These attitudes are not uniformly distributed across the population. As such, this research asks how and why do individuals vary so greatly in their attitudes about science. While previous research proposed measures to quantify scientific attitudes and interests (Fraser, 1981b; Moore & Foy, 1997; Misiti, Shrigley & Hanson, 1991, See Ch. 2), the present body of research suggests that scientific attitudes can serve as both a cause of behavior (e.g., choosing to study a science, technology, engineer, or math major; hereafter STEM) as well as a dependent variable (i.e., influenced by personality traits, cognitive ability, and motivational interests). To provide an intuitive understanding of how scientific attitudes develop, any research must investigate the aspects that influence scientific attitudes and investigate how they differ among individuals to be properly descriptive of the dimensions of scientific attitudes. This research draws on the psychology of individual differences, or differential psychology, which focuses on the assessment of abilities, personality traits, and interests. Individual differences are the psychological properties that make an individual unique in the domains of personality, cognition, and interests. Taken together, these domains comprise our framework and will shed light on the various influences on individuals' scientific attitudes and interests.

This dissertation will extend previous research on scientific attitudes in several ways. First, the psychometric assessment of scientific attitudes allows future researchers to demonstrate predictive validity by assessing future outcomes (e.g., looking at the impact of positive attitudes toward science on education and vocational outcomes) in addition to the concurrent validity of present attitudes (e.g., investigating the mean-level differences between STEM and non-STEM majors or occupations) of scientific attitudes. Second, by adopting a framework of differential psychology, this research uncovers the latent associations between scientific attitudes and personality traits, cognitive abilities, and motivational interests. We unmask why some choose to pursue scientific majors and delight in scientific occupations. Previous evidence has made clear that individual differences supply a better understanding of academic achievement (Benbow & Stanley, 1996), cognitive ability (Ackerman, 1996), and creativity (Eysenck, 1995) than disciplines which ignore the within-person variability of these constructs. Without paying attention attention to the constellation formed by various individual differences, researchers are blind in the night sky as the causal pathways that influence scientific attitudes remain undetermined. In this alternative, researchers are impeded by focusing on only the attitudes as the sole objects of interest instead of the underlying traits that determine the attitudes. Finally, this dissertation hopes to aid researchers in attracting young minds to scientific disciplines, generating countless amounts of research. Based on the present set of studies, future research is well positioned to ask questions such as, 'At what age do scientific attitudes coalesce and how should this result inform public policy toward STEM education?' using the newly validated measure. By providing a definitive answer to this question, designs for STEM interventions are more targeted and will achieve greater effects.

1.1. Science's relationship with society

Past research has shown that science has a complex relationship with society. On one hand, society enjoys the technological benefits that scientific research provides and appears to value interest in STEM careers. For example, in 2010 President Obama organized the first White House Science Fair, an event designed to promote scientific interest in children. Similarly, politicians and educators are alarmed by test scores demonstrating that America is falling behind its peers in STEM education (Drew, 2011) and scientific leaders, such as astrophysicist and popularizer of science Neil deGrasse Tyson, have repeatedly voiced their concern about the decreasing funding for American science programs (Chang, 2012). In sum, the importance of positive attitudes toward science and scientific funding in the United States are generally agreed to be paramount to its future as an innovative economy.

On the other hand, our relationship with certain aspects of science, such as evolutionary theory, is contentious as students, educators, and the public find the theory difficult to accept (Evans & Lane, 2011; Evans, 2001; Abrie, 2010). For example, evidence from Evans and colleagues points to large, culturally-partitioned attitudes that predict the acceptance and knowledge of evolutionary theory. One study on the emergence of beliefs about the origins of species found sharp religious divides, controlling for age, education, and locale (Evans, 2001). Children's religious interest predicted their evolutionist or creationist beliefs, over and above parental beliefs, causing them to privilege certain beliefs and inhibiting others. Clearly, attitudes about scientific topics are sensitive to differences in attitudes and interests.

One way of improving scientific attitudes and interests is to discover why some individuals become interested in science and which factors affect the types of attitudes the public holds toward science. Indeed, adopting an individual differences framework to study scientific outcomes can have very specific implications for public policies at all levels, from school children to adults. For example, another study on individual differences in science text comprehension using high- and low-cohesion text looked at cognitive ability, conscientiousness, and science self-efficacy in students (Hall, Basran, Paterson, Kowalski, Filik & Maltby, 2014). Results indicated that low cognitive ability was associated with poor performance on understanding low cohesion text, low self-efficacy with only average performance on understanding low-cohesion text, and low dutifulness (i.e., a facet of conscientiousness) was also associated with poor understanding low cohesion situations. Thus, to maximize the ability of struggling students to understand the basic science, Hall et al. (2014) suggest that highly cohesive science textbooks can increase text comprehension for certain students.

If we agree individual differences in personality traits, cognitive ability, and motivational interests are important characteristics that affect the development of scientific attitudes and interests, there are three central problems that this model needs to address. First, a suitable measure of scientific attitudes must be developed that displays high reliability and is empirically derived from items similar to existing measures in use. While many measures have been proposed (see Ch. 2), they are rarely validated and this work aims to improve them. The second problem concerns the lack of convergent validity of scientific attitudes with current measures of personalty traits, cognitive ability, and motivational interests (hereafter TAI). While some studies support the associations with individual facets of the TAI framework, few have investigated all associations concurrently, which would allow us to demonstrate incremental validity in measuring scientific attitudes (and therefore reason to not simply measure TAI). Last, any claim about the development of scientific attitudes over time will need to stem from a longitudinal dataset. This dissertation aims to address the first two problems in subsequent chapters and setup a design which will address the third using a another dataset.

1.2. A new perspective on scientific attitudes: Personality, ability, and interests.

> No one is born a scientist, but some are born with talents and temperaments that form the foundation for doing science. In some children, these talents and aptitudes are manifested very clearly and very precociously.
>
> *Feist & Gorman (1998, p. 5)*

1.2.1. Overview of Individual Differences

Differential psychology is the study of abilities, personality traits, and vocational interests using psychometric techniques, with emphasis put on their causal and developmental pathways (Lubinski, 2000; Revelle, Wilt & Condon, 2011). Because differential psychology draws on many disciplines, its scholars have many areas of expertise: "Differential psychology requires a general knowledge of all of psychology for people (as well as chimpanzees, dogs, rats and fishes) differ in many ways. Thus, differential psychologists do not say that they are cognitive-psychologists, social-psychologists, neuro-psychologists, behavior geneticists, psychometricians or methodologists, for although we do those various hyphenated parts of psychology, by saying we study differential psychology, we have said we do all of those things." (Revelle et al., 2011, p. 1). The establishment of differential psychology was at one time called the greatest acheivement of the American Psychological Association (Scott, 1920). Early treatments of individual differences by scholars such as Willerman (1979) provided the foundation for psychologists across divisions to adopt the framework. Today, broad empirical evidence supports the position that differential psychology has broadened our knowledge of academic acheivement (Benbow & Stanley, 1996), intelligence (Ackerman, 1996), creativity (Eysenck, 1995), job performance (Barrick & Mount, 1991), and numerous other real-world outcomes. The following sections outline each of the areas of differential psychology, namely personality, ability, and interests, and highlight their significance to scientific attitudes and vocations.

1.2.2. Personality

1.2.2.1. What are modern definitions of personality? Our modern definition of personality takes root in classical times. Early models of personality were typological rather than dimensional and attempting to place individuals into discrete categories (Revelle et al., 2011). First, Theophrastus, a student of Aristotle, identified thirty human character types around the 3rd century BC (Rusten, 1993), and likewise, Hippocrates and Galen outlined four types of temperaments which seem to describe the dimensions of neuroticism and extraversion: melancholic, choleric, sanguine, and phlegmatic (Deary, 2009). Although these ideas are quite old, key developments have expanded the use of trait-like language to describe human temperament, including the use of language terms to study temperament (Galton, 1874), the development of trait theory (Allport, 1937), and the development of exploratory factor analysis to empirically identify traits among several items (Thurstone, 1947; Spearman, 1904). In fact, it is possible to organize Theophastus' 'characters' using modern descriptions of personality (Revelle et al., 2011, p. 4).

Modern definitions of personality also use traits as a basic descriptive unit to describe individuals' stable behavior over time in a parsimonious manner. Many definitions have been proposed and, indeed, Allport (1937) asserted this to be a pressing problem. He asserted that: *a*) a trait has more than nominal existence, *b*) is more than a habit, *c*) is dynamic, *d*) is independent of other traits, *e*) is not the same as a moral quality, *f*) are not negated by acts that are inconsistent with the trait, and *g*) can be viewed from within the individual or within a population. His intuition that a trait is more than a generalized habit was also shared by Eysenck (1947, 1953). Similarly, we stand on their shoulders and will define a trait as the general disposition of an individual to act, feel, want, or think in a certain way.

While various trait models have been proposed (see Cattell, 1943a, 1945), there has been a recent convergence on five factors of personality (Goldberg & others, 1990; Digman, 1996), such as the Big-5 (Digman, 1989) or the Five Factor Model as measured by the NEO personality inventory (Costa & McCrae, 1985). These traits have been characterized as openness to experience, conscientiousness, extraversion, agreeableness, and neuroticism, although they are not without criticism. For example, in some cultures, there exists evidence for a sixth dimension comprised of honesty and humility (Ashton & Lee, 2005, 2008). Furthermore, although we talk about the five factor traits as if they are orthogonal, they are not and can be combined into higher-order traits, although the correlations are low (DeYoung, 2006), and divided into lower-order aspects (DeYoung, Quilty & Peterson, 2007). Additionally, although evidence exists for a similar five-factor structure across multiple cultures (McCrae, 2001), it is important to note that these traits are *etic* derivations of Western-based lexicons, rather than *emic* approaches in which the factors are created from the lexicons native to the respective cultures. Despite these criticisms, the five factor model continues to be a popular, stable, and empirically derived description of personality traits. There is evidence that competing constructs, such as the types identified by the Myers-Briggs Type Indicator, correspond to traits within the five-factor model (McCrae & Costa, 1989). Furthermore, cross-cultural support for the five-factor model may be due to our biology, as research has demonstrated the heritability of specific personality traits in both studies of twins and family relatives (Pilia, Chen, Scuteri, Orrú, Albai, Dei, Lai, Usala, Lai, Loi & others, 2006; Ando, Nonaka, Ozaki, Sato, Fujisawa, Suzuki, Yamagata, Takahashi, Nakajima, Kato & others, 2006). As such, the five factors will form the basis for our analysis of the association of personality with scientific attitudes and interests.

1.2.2.2. Personality of scientists. Personality is a particularly effective domain to explore scientific attitudes as both domains are rooted in a common emphasis: the uniqueness of the individual. Research on differences in temperament between scientists and non-scientists dates back to Francis Galton, who published one of the first investigations of the characteristics of geniuses on a sample that included many scientists (Galton, 1874). By examining obituaries and looking at the distribution of specific abilities and qualities between gifted families, Galton concluded that people differ in their abilities and that such differences may be largely innate. For example, Galton asserted that individuals possess differential amounts of *energy*, or nervous force, that may or may not be overtaxed by their daily duties. Men of science were endowed with great amounts of this energy, and tended to work extreme hours late into the night. While scientists have different descriptions for this trait today, we share the intuition that scientific individuals have different dispositions and traits from non-scientists.

More recently, Feist and colleagues have completed more quantitative investigations into the temperamental characteristics of scientists by investigating a more focused sample of occupational scientists and students in disciplines of science, technology, engineering and mathematics (i.e., STEM). Beginning in 1998, researchers conducted a meta-analysis on the association of personality traits with scientific and artistic creativity (Feist, 1998). By mapping psychological traits and scales onto the Big 5/Five-Factor Model of personality (Goldberget al. , 1990; Digman, 1990; McCrae & Costa, 1987), Feist explored the differences between scientists vs. non-scientists, creative vs. less-creative scientists, and creative artists vs. less-creative artists. Results revealed that the scientists in the sample were less open, more conscientious, and extraverted (specifically confident) than non-scientists when measured by scaled consistent with the five-factor model. Similarly, scales on the California Psychological Inventory that distinguished scientists vs. non-scientists most clearly were *achievement via independence*, *achievement via conformance*, *psychological mindedness*, and *sociability* (Gough, 1990). Overall, creative individuals are higher on introversion, openness to experience, conscientiousness, and autonomy than non-creative individuals. However, patterns were different for creative *artists* vs. creative *scientists*. Artists were less emotionally stable and more likely to reject group norms than scientists. Thus, while there appears to exist a trait profile for creative individuals, it differentiates at the lower-level for scientists vs. non-scientists (see Table 4 in Feist, 1998).

Similiarly, a recent study on college students predicted levels of interest in science using personality dimensions (Feist, 2012). Feist compared college undergraduates on personality dimensions of openness to experience, conscientiousness, and introversion as well as *need for cognition*, a congitive style associated with openness to experience. He concluded that both personality and need for cognition relate to students' scientific attitudes and interests. Specifically, openness to experience, introversion, and conscientiousness were all correlated with scientific interests.

Although traits provide a framework to explain individual differences, another review argues that researchers must draw on two disciplines to explore the nature of scientific interest, developmental and personality psychology, and makes a persuasive argument that both impact scientific interests (Feist, 2006; Feist & Gorman, 1998). First, Feist explores familial (e.g., birth-order, immigration status), gender, and age influences on scientific interests and talent. Some particularly interesting findings are that scientists were reported to be more likely to be first-born children (Galton, 1874). As research into birth-order effects continues (Damian & Roberts, 2015a), it is possible that these early findings were due to differences in intellectual ability or select personality traits. Additionally, more eminent scientists have foreign-born parents (Terman, 1954). However, this effect may not hold up today and may have been due to the educated refugees fleeing Germany (Sulloway, 1996). In addition to birth order and parental background, therefore is also an influence of parents, teachers, and mentors on scientific ability. Teachers and families who value educators are important for developing a positive attitude toward science (Subotnik, Duschl & Selmon, 1993). Similar to his previous empirical findings, Feist suggests that individuals who are higher on traits of openness to experience, conscientiousness, and dominance are high in their scientific interest (Feist & Gorman, 1998).

Being extraverted was associated with interest in social science, while being introverted was associated with interest in physical science. In sum, scientists are not just individuals with particular patterns of psychological traits but often particular developmental histories in which the presence of certain traits early on may lower the threshold to paths of scientific interest. This idea is consistent with Ackerman's theory of intellectual development (process, personality, interests, and knowledge theory; PPIK), in which cognitive ability is directed into certain developmental pathways by personality traits and interests. In sum, there exists broad evidence that individual differences in personality traits are associated with scientific attitudes and interests, and that the effect of these traits may be asserted developmentally.

1.2.3. Cognitive ability

1.2.3.1. What is cognitive ability? Although the verbal definition of intelligence is still being debated (Meehl, 1998), there are generally two components of "intelligence" that Reeve & Bonaccio (2011, p. 189) describe as *a*) "the ability to learn new things and solve novel problems (i.e., abilities; fluid intelligence)" and *b*) "the outcomes of learning, namely the achievement of acquired knowledge and skills, which are dependent on prior experience within a specific cultural context." *Intelligence* has also been referred to as "the capacity to acquire knowledge" and individuals' ability to solve novel problems (Snyderman & Rothman, 1987). These verbal definitions are modeled nicely by the concepts of fluid intelligence (i.e., g_f) and crystallized intelligence (i.e., g_c), both subcomponents of *g*, or general intelligence (Horn & Noll, 1997; Cattell, 1943b). Researchers prefer hierarchical models of intelligence because they accurately explain the positive manifold between smaller mental tasks (Carroll, 1993). That is, individuals who perform well on one type of mental task generally perform well on others due to the "conspicuous red thread running through variegated conglomerations of cognitive tests" (Lubinski, 2000). While many psychometric models of intellect differ from Carroll (1993), most support a hierarchical view of cognitive ability in which *general intelligence* is found at the top of the hierarchy, representing communality between all subcategories. *g* is then split into secondary abilities in the second tier (e.g., mechanical/spatial reasoning, mathematical ability, and verbal reasoning). The secondary abilities can then be further split into specific tests (e.g., 2D mental rotations, vocabulary, etc.). Other proposed models include a 2 dimensional model with *a*) a general factor, and *b*) a bipolar verbal-spatial factor (Eysenck, 1995) , as well as another 2-factor model which groups tests into *a*) a verbal-educational-numerical factor, and *b*) a mechanical-spatial-practical factor (Vernon, 1960) . More recently, Johnson & Bouchard Jr (2005) proposed the verbal-perceptual-rotation model, in which *g* unfolds into distinguishable abilities which then unfold onto broader stratum.

Although it may seem that breaking intelligence into subcomponents avoids an elegant solution to the problem, this allows researchers to demonstrate the *incremental validity* in the predictive power of the lower-order abilities over and above general intelligence. Differential psychologists have noted the danger in selecting models that simply account for the greatest amount of common variance (McNemar, 1964; Humphreys, 1962; Lubinski & Dawis, 1992). With respect to the domain of individual differences, while general intelligence may account for 50% of the variance among aptitude tests, it is also a useful exercise to ask if there are aspects of it (e.g., spatial intelligence) that are particularly important for predicting an outcome *over and above* general intelligence. However, too much focus on its definition could distract from the predictive power of the many empirical findings. I argue that given a hypothetical graph where the x-axis represents time and the y-axis knowledge, while knowledge may be the area under the curve (i.e., $\int \Delta Knowledge\, \partial Time$), ability is instead the slope (i.e., $\Delta Knowledge$), or speed at which one can learn. While my example is simplistic, it is sufficient for this body of work.

The science of cognitive ability perhaps began with Galton, whose studies on individual differences in intellectual achievement helped found the successful scientific effort (Galton, 1869, 1874). However, it wasn't until later using psychometric techniques pioneered by Spearman (1904) and Binet & Simon (1916) that psychologists could explore general mental ability in a quantifiable, systematic fashion, extracting Spearman's *g* from various mental tasks. Not everyone agreed with the existence of a general factor, a debate that continues today. Thurstone (1938) posited the existence of 7 orthogonal primary mental abilities (i.e., PMAs). However, in a twist of irony, if Thurstone had selected the correct factor rotation, *g* can indeed be extracted from his data (Spearman, 1939). These early efforts and debates paid off. To date, a bounty of evidence exists on the nature and development of intelligence, sources of individual differences, and the impact of intelligence on one's health, occupation, and education (Reeve & Bonaccio, 2011).

Research on cognitive ability continues today in part due to its demonstrated predictive validity. That is, valid tests which index cognitive ability have successfully predicted a range of important social outcomes. For example, cognitive ability has been shown to predict general education outcomes (Gottfredson, 1999; Benbow & Stanley, 1996; Snow, 1996; Lubinski, Webb, Morelock, Benbow & others, 2001; Kell, Lubinski & Benbow, 2013; Wai, Lubinski, Benbow & Steiger, 2010), job performance (Schmidt & Hunter, 2004, 2000, 1998), health outcomes (Gottfredson, 2004; Gottfredson & Deary, 2004; Lubinski & Humphreys, 1997), and even propensity to motor vehicle accidents (O'Toole, 1990). Although some studies report different correlation strengths between cognitive ability and similar outcome variables, such as job performance, it is important to note that this doesn't affect the overall generalization drawn from these sets of studies. The relationship between cognitive ability (X) and job performance (Y) is moderated by the complexity of the job (Z), such that more demanding job categories display stronger relationships between cognitive ability and job performance (Lubinski, 2000). The same moderation effect exists between cognitive ability and academic learning, as the strength of the relationship depends on the time in which one has to learn the material (Benbow & Stanley, 1996).

This approach to studying intelligence is called the *psychometric tradition* - but it is not the only one. The psychometric tradition attempts to discover the nature and true number of basic cognitive abilities. It uses factor analysis and multidimensional scaling to reduce dimensionality, and various rotations for interpretation to look for the common variance accounted for among multiple types of taxing mental operations. In contrast, others have taken a developmental perspective and are instead concerned with the nature of acquired intellect. However, it is important to note that these two approaches aren't necessarily competing. Horn (1968) integrated the psychometric model with a developmental approach. Similarly, the PPIK is a more recent attempt in which temperament and interests act as pathways for intelligence, which gives rise to domain specific knowledge and interests (Ackerman, 1996). When I talk about cognitive ability, I am referring to the generalizable, latent construct of the psychometric tradition that gives rise to individual differences in domain specific knowledge, such as science.

1.2.3.2. Association of cognitive ability and science. There is substantive evidence to support the association between cognitive ability and scientific interests, whether at the level of college discipline, vocation or achievement (Lubinski, Benbow, Webb & Bleske-Rechek, 2006; Lubinski et al., 2001). Two studies on a longitudinal cohort looked at accomplishment in science, technology, education, and math (i.e., STEM) (Wai et al., 2010). The sample was initially comprised of precocious 13-year-olds who had scored greater or equal to 500 on the SAT - Quantitative. Not only did the gifted students pursue STEM majors and vocations at greater rates than their normative peers, but among the gifted students, those who engaged in more pre-college STEM education were more likely to pursue STEM majors and careers, suggesting an interaction between intelligence and interests. Similarly, recent evidence suggests that cognitive ability plays a role in the number of accomplishments garnered. A follow-up study on the same sample of precocious 13-year-olds concluded that they were more likely to choose prestigious occupations and be employed by impressive institutions at age 38 than graduate students at prestigious universities (Kell et al., 2013). For example, more than 7% of the sample received tenure at research-intensive universities. Taken together, cognitive ability is important not only in the pursuit of a STEM education and vocation but also for success within that vocation as measured by the number of accomplishements.

However, spatial ability is another important source of individual differences that has been historically neglected. A review of 50-years of longitudinal research highlighted the role of spatial ability in STEM education, pointing out that individual differences in spatial ability can help inform known aptitude by treatment interactions (Lubinski, 2010). Specifically. Lubinski argues that spatial ability is crucial for talent identification and that selecting STEM students without considering spatial ability may be pointless. Another recent longintudinal study of the same precocious 13-year-olds investigated whether spatial ability differentially predicted successfully holding a patent or refereed publication, over and above the SAT math and verbal subtests (Kell, Lubinski, Benbow & Steiger, 2013; Kell & Lubinski, 2013). While SAT math accounted for 10.8% of the variance, spatial ability accounted for an additional 7% of the variance. The authors conclude that spatial ability plays a unique role in measured creativity, over and above the typically measured abilities.

In sum, any investigation of scientific attitudes and their development must clearly account for individual differences in ability. Cognitive ability plays a large role in STEM outcomes, and any thorough investigation of the development of attitudes over time must residualize for its effects.

1.2.4. Interests

> “Interests energize and direct action toward attaining and maintaining environments best suited to fulfill the individuals’ needs. In that sense, interests describe the means by which and the environments in which people can function optimally.”
>
> *Armstrong, Su, & Rounds (2011, p. 626)*

1.2.4.1. What are interests? In this section, I review the historical background and modern conceptions of interests, building further support for my model that scientific attitudes are a function of temperament, ability, and interests, or $SA = f(T, A, I) + \epsilon$. Scientific attention to measuring interests, values, and preferences has a rich history. Taken together, this triad reflects important differences between individuals and shed light on the reasons we have for acting in a particular manner. Interests have been the popular topic of study for many applied psychologists, dating back to the formation of the first *applied psychology* unit by the Carnegie Institute for Technology and its publication of the Carnegie Interest Inventory (Spearman, 1910; DuBois & Garson, 1970, hereafter CII;). However, the measurement of interests using an inventory is be possible due to the important works of Binet, Galton, Pearson, and Spearmen. While the latter three individual difference psychologists expanded upon using the correlation coefficient to analyze data sets and make empirical claims, Spearman's insight was that the aggregation of indicators lacking reliability could yield a reliable and valid test as a whole (Dawis, 1991). The development of interest measures continued at a rapid pace. In 1927 the Strong Vocational Interest Blank (SVIB) was published by E. K. Strong while working at the Carnegie Institute of Technology. Strong's insight was that different occupational groups responded in differential patterns to the CII and expanded upon this initial finding. Strong wasn't the only prominent psychologist to publish and influential measure of individual differences in motivation. In the 1930s, Allport and Vernon published the Study of Values (Vernon & Allport, 1931), which was followed by the Kuder Preference Record (Kuder, 1934). The Study of Values differed from the SVIB in that it did not focus on differences between individuals by ascribing profiles but instead focused on differences within individuals by assigning normative scores. This technique of using ipsative scores and forced choice items remains popular today with many inventories.

However, theorizing about the structure of interests and the cognitive processes by which they operate was held off until the 1960s. The RAISEC model remains popular today and focuses on matching individuals to environments (Holland, 1997). It divides vocational interests into six categories: *a*) realistic, *b*) investigative, *c*) artistic, *d*) social, *e*) enterprising, and *f*) conventional. Under RIASEC, people with different personalities prefer different work preferences and work activities. An individual may be given three letters that correspond to his highest three interests. As vocations can also be organized in the same factor space and given three letters, individuals can be matched with various vocations based on their fits. It's important to note that vocational interests, even when organized into the RAISEC categories, are associated with personality traits. Specifically, one study asserted that sociability and conformity underly the vocational choices and can be overlayed onto the model once it is organized into a circumplex (Hogan, 1983). In the present set of studies, I use the Oregon Vocational Interest Scales (i.e., ORVIS) (Pozzebon, Visser, Ashton, Lee & Goldberg, 2010). It is a public-domain scale that has high internal-consistency properties. Similar to the RIASEC, vocational interests are divided into eight scales: *a*) leadership, *b*) organization, *c*) altruism, *d*) creativity, *e*) analysis, *f*) producing, *g*) adventuring, and *h*) erudition. In conclusion, the development of interest scales has yielded numerous reliable, valid measures that help researchers understand the different fits between personalities and their environments.

1.2.4.2. Scientific interest. Interests are of particular importance for STEM education as they are typically viewed as less stable than ability or personality traits (Roberts, Walton, Viechtbauer & others, 2006) and therefore a potentially important target for STEM interventions. For example, evidence suggests that interests are influenced over time by family, school, and culture (Eccles, Midgley, Wigfield, Buchanan, Reuman, Flanagan & Mac Iver, 1993). More importantly, we also know that there are wide ranging differences on measures of scientific interests. For example, one study investigated students' attitudes toward science using the Test of Science Related Attitudes (i.e., TOSRA) (White & Richardson, 1993). Researchers found differences by age, ethnicity, and gender on the TOSRA. Luckily, these differences in scientific attitudes can be influence. Research on students' learning stategies suggests that teaching using metacognitive tools rather than rote memorization can positively influence scientific attitudes

(Edmondson & Novak, 2006). Additionally, there is evidence that the classroom environment plays an important role in attitude formation. Past research on high-school chemistry students found that the nature of the science laboratory influenced cognitive and affective outcomes, including four attitudinal measures, controlling for differences in general ability (McRobbie & Fraser, 1993).

In sum, temperament, ability, and interests all play a role in determining individuals' attitudes toward science and interest in studying science. Any cohesive study of scientific attitudes must then situate itself within a framework of individual differences. In doing so, we may understand how and why individuals vary so greatly in their scientific attitudes and shed light on the best ways to positively influence them.

1.3. Description of Studies

1.3.1. Chapter 2: Designing a better measure of scientific attitudes

Without a reliable and validated assessment of scientific attitudes, no further attention can be given to their association with other psychological constructs or the impact of scientific attitudes on socially valued life outcomes. Therefore, in Study 1 a psychometric assessment of the SAI-II is performed which evaluates the factor structure and the quality of the items. In doing so, we discover how many underlying factors account for the individual differences in students' scientific attitudes in a parsimonious manner. Second, item-response theory is used to eliminate poorly performing items within the test. Study 1 concludes by recommending a newly revised and validated version of the Scientific Attitudes Inventory - Revised.

Study 2 assesses the structural properties of the SAI-II revision against a broad, online sample.

1.3.2. Chapter 3: Demonstrating the concurrent validity of scientific attitudes using temperament, ability, and interests.

Given that temperament, ability, and interests are all important in determining scientific interests and attitudes, the purpose of Chapter 3 is to establish concurrent validity using validated measures of personality traits, cognitive ability, and vocational and avocational interests. Additionally, it attempts to establish construct validity be looking at differences in scientific attitude scores by college discipline to look for differences between STEM and non-STEM disciplines.

1.3.3. Chapter 4: Investigating the importance of scientific attitudes over time using Project TALENT

The purpose of Chapter 4 is to replicate the association of scientific attitudes with temperament, ability, and interests using Project TALENT. Project TALENT is a national longitudinal study that surveyed high-school students beginning in 1960 that investigated students' interests, career plans, temperament, and life objectives. It was designed to be representative of the US population and sampled across economic, cultural, social, and urban backgrounds.

Project TALENT was designed before the popularity of our measures of temperament, ability, and interests. First, can we psychometrically organize its temperament and vocational interests scales into factor structures that allow for comparison with the findings of Chapters 2 and 3? To organize our vocational interests, we look to previous work by Low, Yoon, Roberts & Rounds (2005). Second, can the scale associations from Chapter 3 (i.e., SAI & TAI) be applied to the Project TALENT cohort and do we observe similar fit indices? Project TALENT has included several measures of temperament, many different types of abilities, and vocational interests. Additionally, they have several variables which correspond to positive attitudes about science. While the constructs are different, we look for a similar model across a different item set - not entirely unlike the extraction of Spearman's g from the Thurston's PMAs.

In sum, the analyses in Chapter 4 will replicate the scale associations found in Chapter 2 in the Project TALENT dataset.

CHAPTER 2

Evaluating the Scientific Attitude Inventory - Revised

2.1. Abstract

Scientific attitudes refer to the interaction of affect, behavior, cognition, and desires as they relate to opinions of science. The Scientific Attitude Inventory - Revised (SAI-II) seeks to assess the dimensions of attitudes toward science. While its original authors proposed scoring the inventory as a single dimension (Moore & Foy, 1997), research has questioned whether scientific attitudes are unidimensional (Lichtenstein, Owen, Blalock, Liu, Ramirez, Pruski, Marshall & Toepperwein, 2008). To date, its structure and applicability to college-aged samples remain undecided. In two studies, we examined the psychometric properties of the SAI-II using factor analysis and item response theory. Study 1 (N = 301, 134 men) supported a 4-factor structure in which many items had good discrimination and high item information values. Study 2 (N = 2,324, 808 men) attempted to replicate the structure of Study 1 and examined its validity using a diverse online sample. Our results suggest interpreting the SAI-II as a multidimensional assessment. We provide a recommended short form which removes bad items with low factor loadings. Future work should measure the stability of scientific attitudes over time and their influence on dispositional traits.

2.2. Introduction

Since Galton (1874) first reported on the characteristics of scientists, many wondered how the attitudes and characteristics of scientists differ from non-scientists (Eysenck, 1995; Kell et al., 2013; Ferriman, Lubinski & Benbow, 2009). An important issue is how to measure scientific attitudes, as positive scientific attitudes help predict who participates in science related activities, such as robotics competitions (Welch, 2010), as well as overall achievement in science (Oliver & Simpson, 1988).

Given the importance of scientific attitudes for success in scientific achievement, it is not surprising that multiple measures have been proposed for its assessment. These scales include the (a) Test of Scientific Thinking (Noll, 1935), (b) the Scientific Attitude Inventory (Moore & Sutman, 1970), (c) the Test of Science Related Attitudes (Fraser, 1981b), (d) the Test of Scientific Attitude (Miller, 1983), (e) the Science Attitude Scale (Misiti et al., 1991), and (f) the Scientific Attitude Inventory - Revised (Moore & Foy, 1997). Of these measures, one of the more widely cited is the Scientific Attitude Inventory (i.e., SAI; Moore, 1970). To date, very little psychometric and validity data has been published on this scale or its more recent revision. Despite confusion regarding the psychometric properties of the SAI-II, it remains in use today (Nadelson & Sinatra, 2010; Feist, 2012). We provide a brief review of the scientific attitudes literature before proceeding to a psychometric analysis of the SAI-II and conclude by recommending an item response theory (Embretson & Reise, 2013) informed abbreviation of the SAI-II and proposing several potential applications.

Measuring Scientific Attitudes

To measure scientific attitudes, many inventories have been developed to assess an individual's affect, behavior, and cognition, and desires toward scientific theory and related activities. The original Scientific Attitude Inventory assesses students' beliefs and attitudes toward science using 60 Likert-type items organized around 12 position statements representing the bipolar ends of 6 subscales (i.e., 2 position statements per subscale) (Moore, 1970). The 12 position statements included issues related to desire to practice, propensity to trust in, and openness to science, such as "The laws and/or theories of science are approximations of truth and are subject to change.". Each subscale is comprised of items which assess the cognitive and emotional aspects of scientific attitudes. Self-report measures similar to SAI ask the participant to indicate the extent of his or her acceptance with an attitudinal item, leading to a total score. The total score reflects the sum of all items in the test, despite distinct position statements guiding their content development. In sum, instruments similar to the SAI represent attempts to quantify student's attitudes and beliefs toward science to clarify the kinds of people that are interested in science and illuminate what attitudes the public holds toward science.

Both experiments and observational studies widely used the first iteration of the SAI. Cited more than 200 times as of 2017, multiple disciplines used the SAI to explore questions of curriculum evaluation (Fraser, 1981a), science teachers' beliefs (Koulaidis & Ogborn, 1995), and assess changes in attitudes during high school (Siegel & Ranney, 2003). While Moore originally validated the SAI against middle- and high-school students, studies have used it with a range of samples, including college students (Welch, 1972a,b), and adults (Lawrenz, 1975). The use of an instrument with populations for which it was not originally designed is not recommended and we are not the first to raise concerns regarding its validity. For example, two reviews of the 1970 instrument raised a number of concerns regarding the validity of the SAI (Munby, 1983; Nagy, 1978). In reviewing 30 studies which used the SAI, Munby found that many items could be interpreted differently due to double-barreled wording and ambiguity (e.g., "Every citizen should understand science because we are living in an age of science"). The researcher cannot ascertain if the participant agrees with the beginning or end of the position statement.

Furthermore, a number of questions suffered from gender-bias, such that we expect males to score higher than females. The observation that many studies employed the SAI without adequate consideration of its reliability or validity concerned Munby and concluded that it needed revision. Munby's review found that the average test reliability between studies was less than satisfactory, leading him to conclude that a research cannot ascertain what is being measured and that the SAI was in need of "conceptual rebuilding" (Munby, 1983, p. 158).

Moore & Foy (1997) later revised the original instrument and responded to the criticisms by Munby (1983) regarding its validity by producing a revised instrument. The new revision (i.e., SAI-II) included a subset of 40 of the original 60 items and rephrased 30 questions due to gender bias. The 40 attitude items were developed around the original 12 position statements for a total of 40 possible Likert items (see Tables A.2 and A.3 on pages 117 and 118). Additionally, the original instrument was edited to ensure ease of readability. Its 1997 revision (i.e., Moore & Foy, 1997) has proved similarly popular, garnering over 200 citations according to Google Scholar as of 2017. However, a fraction of these studies used the SAI-II to measure attitudes. This may be due to increased awareness of the importance of instrument validity raised by Munby (1983).

When publishing the revision, Moore & Foy did not include important parts of their original analysis, such as the psychometric properties and factor structure of the questionnaire. When Moore & Foy analyzed their data, they did not report their 1- and 2-factor confirmatory analyses due to poor item loadings. Additionally, an exploratory factor analysis produced a 5-factor solution, which they disregarded in favor of the structure produced by their content judges due to their inability to give the factors meaningful names. We believe the choice of the original authors to not disclose the factor analytic results undermines the usefulness of the SAI and SAI-II and seek to address this shortcoming in the present studies.

Previous Evaluation of the Scientific Attitude Inventory - Revised (SAI-II)

The lack of validation of the SAI-II concerned other researchers as well. Recently, Lichtenstein et al. (2008) evaluated the psychometric properties of the SAI-II using middle- and high-school students. The 12 position statements guiding development of the items for the SAI and SAI-II were interpreted by Lichtenstein et al. (2008) as evidence for a proposed 12-factor structure. Exploratory factor analysis did not support the hypothesized 12-factor structure.. At the same time, neither did it support a 1-factor solution, indicating that the instrument should not be scored as one test, as Moore & Foy indicate, and that there are multiple independent dimensions to scientific attitudes. Results from the psychometric re-evaluation by Lichtenstein et al. revealed a 3-factor solution which they concluded did not fit well ($\chi^2(321) = 646$, $p < .001$; CFI $= .81$), although alternative measures of model fit were adequate (e.g., RMSEA $= 0.061$). Lichtenstein et al. labeled the three dimensions (a) science is about understanding and explaining, (b) science is rigid, and (c) I want to be a scientist. Similarly, in the present paper we propose a 4-factor solution that supports the content validity of two of Lichtenstein et al's factors, understanding science and desiring to be a scientist. Lichtenstein et al. (2008) conclude that while many of the individual items have merit, the structural interpretation by Moore and Foy may be incorrect and that a reevaluation of the instrument could shorten it and make it more feasible to use.

Given the results of Lichtenstein et al., one central purpose of this paper is to reevaluate the SAI-II and its concurrent validity with choice of academic major using factor analytic techniques in conjunction with item response theory (Embretson & Reise, 2013). We believe we are first in validating the instrument with college students and adults and hope that our findings promote the future use of the instrument with such populations. We conclude our validation by recommending a revised form of the SAI-II (i.e., SAI-III; see Appendix) for use by psychologists and science educators.

Present Study

First, we attempt to replicate and extend Lichtenstein et al.'s research on the SAI-II by examining the factor structure of the instrument with two different adult populations. Based on Lichenstein's work we expected that a single factor would not adequately capture the nature of the scientific attitudes. Additionally, we are the first to examine the factor structure of this instrument in adult populations as earlier versions have primarily been tested on adolescent populations. Second, using item response theory we sought to exam whether the validity of the instrument could be improved by the elimination of certain items. Given past reports of poor factor loading (Lichtenstein et al., 2008), we expected that reducing the number of items might improve the factor-analytic model.

Study 1: Psychometric Analysis of the Scientific Attitude Inventory-Revised (SAI-II)

Method

Participants. Three-hundred and one individuals participated in the study, of whom 134 were men. Following permission from the Institutional Review Board, participants were recruited from the participant pool of an introductory psychology course at Northwestern University. Participants received course credit as compensation. To achieve an exempt IRB status, identifying information such as participant's exact dates of birth were replaced by their year of birth. Their approximate ages ranged from 17 to 34, with a mean age of 19.58 years ($SD = 1.73$). Reported ethnicities were 7.00% Black/African-American, 11% Chinese, 1% Japanese, 11% Korean, 5% Indian, 1% Other Asian, 3% Other Hispanic/Latino, 4% Mexican/Mexican-American, 51% White, 1% Other, 6% Two or more ethnicities.

Additionally, the sample was comprised of 172 freshman, 69 sophomores, 25 juniors, 25 seniors, and 2 graduate students (see Table A.1). Of the 301 participants, 7 did not complete the SAI-II and were excluded from further analysis.

Measure. The Scientific Attitude Inventory - Revised (SAI-II) is a 40-item measure organized around 12 bipolar statements (for item information see Table A.2 on page 117 and Table A.3 on page 118). As we were interested in assessing the structure of the test and the degree to which the items are organized around the position statements, we opted to include the 12 position statements in our assessments for analysis. Each item was scored using the five point Likert-like scale proposed by Moore & Foy (1997), ranging from 1 ('Strongly Disagree') to 5 ('Strongly Agree').

Procedure. Participants completed the SAI-II individually during a one-hour session supervised by either the lead or second author. In addition to the SAI-II, participants completed a demographics questionnaire, the Shipley Institute of Living Scale 2 (Shipley, Gruber, Martin & Klein, 2010), and the 16-item sample test from the International Cognitive Ability Resource (available as Appendix A in Condon & Revelle, 2014) in a block randomized order to control for presentation pattern effects. Additionally, the question order of the SAI-II was also randomized to prevent fatigue and learning effects. Doing so ensured that any missing data were missing completely at random and wouldn't necessarily need to be eliminated from analysis.

Participants were seated in a quiet testing room along with up to 3 other participants, each seated at their own computers and desks with an experimenter present in the room. With the exception of the Shipley Institute of Living Scale 2, all responses were collected using Qualtrics, an online research survey website.

Analyses. Exploratory factor analyses (hereafter EFA) were performed on polychoric correlation matrices in order to examine the structure of the SAI-II. Although it is arguable that confirmatory factor analysis should be preferred over exploratory analysis as theory guides it, there exists no consensus for the lower-order structure of the SAI-II. Therefore, EFA is more appropriate than CFA due to the number of alternative models that result from the SAI-II item pool (see Fabrigar, Wegener, MacCallum & Strahan, 1999; Roberts, Chernyshenko, Stark & Goldberg, 2005). Factor analyses performed on polychoric matrices provide more accurate representations of the latent structure, although the fit statistics may be worse than those provided by Pearson-based fits (Timmerman & Lorenzo-Seva, 2011). However, the magnitude of the difference is influenced by the sample size (see Garrido, Abad & Ponsoda, 2013). EFA models were tested using the `psych` package (Revelle, 2018) in R (R Core Team, 2018). Ordinary least squares was used to fit the data, and model comparison statistics were based on model residuals. Initially, 1- and 3-factor structures were examined to evaluate the SAI-II structures proposed by Moore & Foy (1997) and Lichtenstein et al. (2008), respectively. model did not adequately explain all the items. Similarly, fit statistics for the 1-factor model indicated a bad fit when compared to the more parsimonious models when evaluted using the Bayesian Information Criterion (Schwarz & others, 1978).

One central issue of this study is to identify the number of scientific attitude factors to retain. Several methods were used to determine the most appropriate number of factors. Statistical fits for factor analysis are often determined using the fit function χ^2, which demonstrates whether the residuals are functionally different from 0. As χ^2 is influenced by sample size, we instead opted to use alternative measures of model comparison, such as the root mean square error of approximation (Steiger, 1990, RMSEA), the Tucker-Lewis Index (TLI; Tucker & Lewis, 1973; Hu & Bentler, 1999), the standardized root mean square residual (Bentler, 1995, SRMR), and Velicer's Minimum Average Partial Correlation (hereafter MAP; Velicer, 1976), as well as Horn's Parallel Analysis (Horn, 1965). Other studies have used this approach to comparing model fit as well (Cooper, Gomez & Aucote, 2007; Roberts et al., 2005). As expected, each of these fit measures has a different interpretation for comparing model performance. Specifically, the RMSEA measures the root average squared error of the target model. Values $< .05$ are considered good fits, and values $< .08$ are considered acceptable. The TLI measures incremental improvement the proposed model offers over the null model using their ratios of χ^2 to degrees of freedom (i.e., $\frac{\chi^2}{df}$). Values closer to 1 indicate a good fit. The SRMR is an absolute measure of fit that evaluates the square root of the squared difference of the observed versus predicted correlations, whereby values $< .08$ indicate a good fit. Velicer's MAP selects the model with the lowest average squared partial correlation by iteratively partialling out the principal components and examining the average squared off-diagonal correlation. Finally, Horn's Parallel Analysis examines the factors extracted simultaneously from real and random data, ensuring that the mean eigenvalues of the real factors are always above those extracted from the random data. Typically, factor loadings greater than 0.3 are considered acceptable by researchers. However, Stevens (2002, p. 393) points out that the significance of a factor loading depends on the sample size. We used 0.3 as a critical value.

A second concern of this study is to remove bad items from the pool. A two-parameter (2PL) item-response theory (i.e., IRT) analysis was conducted in R (R Core Team, 2018) using the `psych` package (Revelle, 2018). IRT measures the relationship between individual performance on specific items and overall performance on an ability. Using IRT, we evaluated the unidimensional relationships between the items and several latent factors identified using EFA. As such, we can investigate items which demonstrate poor predictive ability for a given latent trait (See Baker, 2001; Embretson & Reise, 2013).

Results

Tables A.4 and A.5 on pages 119 and 120 provides descriptive statistics for all 40 attitudinal items and 12 position statements on the SAI-II. Mean values indicate the average item scores (from 1 to 5) and ranged from 2.2 (Item 4B) to 4.7 (Item 5).

Structural organization. Exploratory and confirmatory factor analyses of increasing complexity tested predictions about the structure of scientific attitudes as measured by the SAI-II. While previous evaluations were limited to assessing the structure using the 40 attitudinal items, those items were formed using 12 guiding position statements which also provide information regarding one's latent dispositions toward science. For that reason, the following sections present factor analyses using a) the 40 attitudinal items, b) the 12 position statements, and c) the complete 52-item set to provide transparency regarding possible interpretations of the structure. As the attitudinal items were generated from the guiding 12 position statements, we expected to find a similar structure in all 3 subsets of the total item inventory.

Attitude Items. The factorability of the 40 attitudinal items used in previous studies was examined. The Kaiser-Meyer-Olkin (Kaiser, 1970, KMO) measure of sampling adequacy was 0.77, indicating factor analysis was appropriate for these data. Table A.6 and Figure A.1 present the parallel analysis results that informed the maximum number of factors to explore retaining. Column 2 shows the eigenvalues obtained by factoring real data. Column 3 shows the eigenvalues obtained by factoring random data and averaging them. By comparing columns 2 and 3, the parallel analysis indicated up to 9 factors could be retained, although the break in the scree plot suggests a 4-factor solution is more appropriate. Solutions ranging from 1 through 9 factors were examined using oblimin transformations of the factor loading matrix and are reported in Table A.7 on page 122.

First, we discuss the 1-factor structure used for scoring by Moore & Foy (1997). The model's χ^2 indicated the data were not fit by the 1-factor model $\chi^2(740) = 4049.76$, $p < .001$. Both the RMSEA (0.13) and TLI (0.31) indicated a poor fit compared to alternative models. Similarly, the BIC (-173.50) penalized this model compared to models with more latent factors. Given the above model fit statistics, the data do not support the 1-factor interpretation used for scoring.

Second, fit indices for the 3-factor solution preferred by Lichtenstein et al. (2008) were $\chi^2(663) = 2405.53$, $p < .001$, RMSEA $= 0.10$, TLI $=$ 0.59, and BIC $=$ -1378.29. Note that the BIC indicates that this model is not an improvement over 4 through 6 factors, while Revelle's Very Simple Structure prefers the 3-factor solution at a complexity of 1. Although acceptable, the RMSEA value does not fall below 0.10 until at least 4 factors are extracted, indicating greater error. Similarly, the TLI (0.59) suffers compared to models which retain a greater number of factors. Although the 3-factor interpretation is superior to the 1-factor interpretation, the RMSEA suggests that the model residuals could be further reduced to an acceptable threshold by extracting an additional factor.

Iterative exploratory analysis on the attitude items yielded mixed conclusions. While the Very Simple Structure at complexity 1 minimizes with a 3-factor solution, Velicer's MAP achieves a minimum average partial correlation with 4 extracted factors. Extracting 4-factors also yields a BIC below an acceptable threshold of 0.10. In order to decide between extracting 3- and 4-factors, we analyzed both solutions using oblique rotations in minimum residual extraction. Comparing Tables A.8 and A.9 reveals that the large second factor containing high loadings from "Science tries to explain how things happen" and "Good scientists are willing to change their ideas." splits into two smaller factors which reflect an *understanding of science* and *openness to scientific ideas*. Because the two factor extractions produced two similar factors and the 4-factor extraction split the second factor into 2 cohesive factors, we preferred the 4-factor solution.

Position Statements. Next, the factorability of the 12 position statements was examined. To our knowledge, we are the first to analyze the structure of the position statements around which the attitude items were developed. The KMO was 0.57, which is considered 'miserable'. Table A.10 and Figure A.2 present the parallel analysis results that informed the maximum number of factors to explore retaining. The parallel analysis indicated up to 8 factors could be retained, although the break in the scree plot suggests a 4-factor solution is more appropriate. Solutions ranging from 1 through 6 factors were examined using oblimin rotations of the factor loading matrix as more solutions would have resulted in 1-item factors. These results are reported in Table A.11 on page 126.

Exploratory analysis on the position items yielded mixed conclusions. While the Very Simple Structure at complexity 1 achieves a maximum with a 6-factor solution, it is more reasonable to think about a 3-factor solution. Velicer's MAP achieves a minimum average partial correlation with a 1-factor solution. However, unlike the attitude items, the BIC achieves a minimum with a 4-factor solution. Using methods identical to the analysis of the attitudinal items, we examined 3- and 4-factor solutions. Table A.12 on page 127 shows a 3 factors which reflect a) *interest in science*, b) *the utility of science to the public*, and c) *the degree to which scientific ideas change over time*. By comparing this with table A.13 on page 128, we see that the second factor splits, yielding a poor factor with 1-item loading.

Total Item Set. Next, we conclude our exploratory analysis of the structure of the SAI-II by examining the complete correlation matrix, which consists of the attitude items and position statements from the SAI-II. We begin by examining the factorability of the complete matrix. The Kaiser-Meyer-Olkin (Kaiser, 1970, KMO) measure of sampling adequacy was 0.62, which is considered 'mediocre'. Table A.14 and Figure A.3 present the parallel analysis results that informed the maximum number of factors to explore retaining. The parallel analysis indicated that up to 8 factors could be retained, however the sharp break in the scree plot suggested that a 4-factor solution would be appropriate. Solutions ranging from 1 through 8 factors were examined using oblimin rotations of the factor loading matrix and are reported in Table A.15 on page 130.

No clear conclusions could be drawn from the exploratory analysis of the items. While the Very Simple Structure at complexity 1 maximizes with a 3-factor solution, Velicer's MAP minimized with a 6-factor solution. However, unlike the attitude items, the BIC minimizes with a 5-factor solution.

To help decide between extracting the 3-factor model preferred by VSS and the 4-factor model preferred by examining the scree plot, we performed exploratory analyses using methods identical to those used for the attitude and position items. By comparing Tables A.16 and A.17, that the initial second factor containing high loadings from "Science tries to explain how things happen" and "Progress in science requires public support in this age of science; therefore, the public should be made aware of the nature of science and what it attempts to do. The public can understand science and it ultimately benefits from scientific work." splits into two smaller factors which reflect an *understanding of science* and *openness to scientific ideas*. Similar to the results from analysis of the position statements, the factors *interesting in science* and *science leads to answers* remain stable across both solutions while the extracting 4 factors splits the second factor into 2 cohesive factors. Due to the interpretability of the 4-factor solution and smaller model residuals, we again we prefer it.

In sum, the first hypothesis stated that the data would not support the 1-factor interpretation used for scoring by Moore & Foy (1997). Results from the all exploratory factor analyses indicated a poor fit (e.g., χ^2, TLI, & RMSEA). With the each dataset, we performed several exploratory factor analyses with increasingly complex solutions. From these analyses, we concluded that the 4-factor solution provided an empirically and conceptually satisfactory structure. By comparing the 3- and 4-factor solutions, we split the *understanding of science* factor into *understanding* and believing that *science is a valid way to derive answers*. Across item combinations, we found four themes describing a) *Interest in Science*, b) an *Understanding of Science*, c) the degee to which *Science Leads to Answers*, and an d) *Openness to Scientific Ideas* (see Figure A.4 on page 108). The first factor, *interest in science*, was defined by high loadings on *I do not want to be a scientist*, *I would like to be a scientist*, and *Being a scientist is interesting*. Individuals scoring high on this would enjoy doing science as a vocation.

The second factor, *openness to science*, was defined by medium loadings on items *Science tries to explain how things happen*, *Good scientists are willing to change their ideas*, and *Progress in science requires public support in this age of science; therefore, the public should be made aware of the nature of science and what it attempts to do. The public can understand science and it ultimately benefits from scientific work.* Individuals scoring high on this factor are open to the scientific process and its importance for the public good.

The third factor assess the degree to which an individual agrees that *science leads to answers*. This factor was dominated by medium loadings on *Anything we need to know can be found out through science*, *The laws and/or theories of science represent unchangeable truths discovered through science*, *The laws and/or theories of science are approximations of truth and are subject to change*, and *Some questions cannot be answered by science*. While this factor was difficult to conceptually define, an individual scoring high on this factor agrees that science leads to important answers for questions in the natural world and understands that those answers change over time.

Last, the fourth factor assesses the degree to which an individual *understands the scientific process*. *Understanding of science* was defined by high loadings on items *It is useless to listen to a new idea unless everybody agrees with it*, *Science tries to explain how things happen*, and *Public understanding of science would contribute nothing to the advancement of science or to human welfare; therefore, the public has no need to understand the nature of science. They cannot understand it and it does not affect them.* Here, individuals scoring high understand that science is a useful, idea generating activity and that operating in a scientific manner does not require consensus.

Confirmatory Factor Analysis. Next, confirmatory factor analysis (hereafter CFA) was used to test whether a 1-factor structure was an appropriate interpretation for the SAI-II (Moore & Foy, 1997, p. 334) using the *lavaan* package in *R* (Rosseel, 2012). We note that CFA differs from EFA in that one proposes a specified model and measures how well it fits, rather than extracting the best model from the observed correlations. In the first model, latent variables were not constrained to be orthogonal. Fit statistics indicated a poor for for the 12-factor structure, with χ^2(740) $= 2055.84$, $p < .001$, RMSEA $= 0.08$, and TLI $= 0.51$ (ideally $\geq$ 0.95). Additionally, 35 of the 40 attitude items had loadings < 0.3.

The model tested was obtained from the previous EFA - the 4 oblique factors model (Figure A.4). Since the positional statements are important indicators of a participant's latent trait level in addition to their attitudinal statements, the model was fit with all items included. The latent variables' variance was constrained to 1 and orthogonal. Additionally, observed variables were free. The model was identified and included 4 latent variables: a) Interest in science, b) Openness to science, c) Understanding of science, and d) the degree to which science leads to answers (standardized coefficients are provided in Figure **??** and Table A.19). Results indicated that the model was badly fit ($\chi^2(1274) = 2544.92, p < .001.$). While the TLI did not indicate a good fit (TLI = 0.69), the RMSEA indicated an acceptable model fit (RMSEA = 0.06). In sum, this analysis confirmed the hypothesized 4-factor structure found in previous exploratory analyses. However, the model suffered in fit due to low item loadings that can be eliminated in later models.

Internal Consistency. The original authors reported measures of internal consistency for the total test (Cronbach's $\alpha = .78$; Moore & Foy, 1997). Similarly, using factors labeled 'Science is About Understanding and Explaining', 'Science is Rigid', and 'I Want to Be a Scientist', Lichtenstein et al. report alphas of .79, .59, and .85, respectively. However, we note that Cronbach's α is not an appropriate measure of whether a test measures one concept and recommend the use ω_h (Revelle & Zinbarg, 2009), which gives the proportion of variance in scale scores accounted for by a general factor.

Internal consistency measures, such as Omega, were calculated on a 4-factor solution. Although internal consistency would appear to be sufficient (Cronbach's $\alpha = 0.82$), a model based approach to internal consistency (e.g. $\omega_{Total} = 0.86$, $\omega_{Hierarchical} = 0.36$) indicates low general factor saturation, supporting our interpretation of the SAI as a multi-dimensional construct rather than as 1 test. For the individual scales, internal consistency was acceptable for *Interest in Science* ($\omega_{Total} = 0.93$, $\omega_{Hierarchical} = 0.80$), middling for *Openness to Science* ($\omega_{Total} = 0.76$, $\omega_{Hierarchical} = 0.65$), *Science Leads to Answers* ($\omega_{Total} = 0.79$, $\omega_{Hierarchical} = 0.59$), and *Understanding of Science* ($\omega_{Total} = 0.71$, $\omega_{Hierarchical} = 0.46$).

Item Response Theory Analysis. While factor analytic methods demonstrate the degree to which the SAI-II items tap into underlying latent traits, they do not show how well the items perform at various levels of a trait. One of the goals of this paper is to refine the SAI-II by dropping bad items from the administered test. Therefore, item response theory (hereafter IRT) was used to in addition to exploratory factor analysis to refine the scale. IRT provides information about measurement precision across the range of latent traits at both the individual item and SAI-II subscale level, rather than providing a single estimate of internal consistency, such as ω_{total}. Doing so allows the researcher to identify items that contribute little to a scale's measurement. We briefly describe IRT as far as it relates to the interpretation of the tables and figures before continuing with the analysis.

Item response theory relates characteristics of the SAI-II items with the latent traits of the 4 hypothesized subscales, represented by θ_j, in order to predict one's true attitudes about science. In the two-parameter model (2PL), α refers to the item's discrimination. α represents how well the item differentiates among individuals who vary in their attitudes about science. β refers to an item's difficulty, which is a point along the θ axis at which a participant has a 50% chance of responding above a threshold. One seeks to develop scales which have items that discriminate well among varying levels of difficulty on that scale.

IRT analysis was conducted in order to assess hypothesis 2, in which some of the SAI-II items can be eliminated due to poor discrimination and low factor loadings. The IRT outputs of difficulty, discrimination, and information were used to locate poor performing items. The goal was to find a smaller set of items which covered the fullest range of θ (i.e., the measured construct) while also providing good discrimination. A superset of the items which met our criterion (i.e., factor loadings >= 0.4 and good discrimination) are displayed in Table A.15. Item information curves and SAI-II test functions are displayed in Figures A.5. These figures depict the precision by showing the range over θ where an item discriminates best. Tables A.20, A.21, A.22, and A.23 show the item information parameters at varying difficulties in the SAI-II scales. Several items had low information values, indicating that they provided little information across the trait range for individuals. An example of this would be item 33, "The senses are one of the most important tools a scientist has." Additionally, each table shows the TIF and SEM values for the SAI-II factors. The TIF (i.e, test information function) values are relatively high across most of the latent trait for "Interest in Science". Here, test information is higher for negative than positive trait thresholds. The TIF values are mediciore for *Understanding of Science*, *Science Leads to Answers*, and *Openness to Science*, indicated a higher standard error of measurement.

We conclude our IRT analysis by recommending a 27-item revision on Table A.45, which we evaluate in Study 2.

Concurrent Validity. Finally, we investigate whether there is a difference in SAI-II scores between scientific and non-scientific disciplines as declared by participants. Participant majors are grouped into various disciplines (e.g., Undecided, Arts, Business, Communications, Community and Social Services, Computer and Information Sciences, Cultural and Regional Studies, Education, Engineering and Technology, Language and Literature Studies, Mathematics, Medicine and Allied Health, Natural Sciences, Social Sciences). Specific mappings are publicly available at `https://sapa-project.org/data`. The data were dichotomously coded such that "Natural Sciences" and "Social Sciences" were assigned 1, and the other disciplines were assigned 0.

First, a Welch two-samples t-test was conducted to compare SAI-II total scores for scientific disciplines. There was a significant difference in the scores for non-scientific disciplines ($M = 2.89$, $SD = 0.22$) and scientific disciplines ($M = 2.96$, $SD = 0.24$) conditions; $t(205) = -2.56$, $p = .01$. Second, we compared SAI-II Interest scores for scientific disciplines. There was a significant difference in the scores for non-scientific disciplines ($M = 2.86$, $SD = 0.37$) and scientific disciplines ($M = 3.00$, $SD = 0.36$) conditions; $t(226) = -3.25$, $p = .001$. Third, we compared SAI-II Understanding scores for scientific disciplines. There was a significant difference in the scores for non-scientific disciplines ($M = 3.90$, $SD = 0.51$) and scientific disciplines ($M = 4.07$, $SD = 0.49$) conditions; $t(228) = -2.80$, $p = .005$. Four, we compared SAI-II Openness scores for scientific disciplines. There was not a significant difference in the scores for non-scientific disciplines ($M = 1.95$, $SD = 0.37$) and scientific disciplines ($M = 1.90$, $SD = 0.33$) conditions; $t(243) = 1.23$, $p = 0.21$. Last, we compared SAI-II Openness scores for scientific disciplines. There was not a significant difference in the scores for non-scientific disciplines ($M = 2.88$, $SD = 0.39$) and scientific disciplines ($M = 2.85$, $SD = 0.46$) conditions; $t(191) = 0.59$, $p = 0.55$. Results revealed evidence for concurrent validity with SAI total scores, Interest subscale scores, and Understanding subscale cores with participant's choice of a scientific university discipline. See Figure A.7.

Discussion

The present study aimed at the revision and psychometric improvement of a previously developed measure of scientific attitudes. The results of the structural validation study set the path for future work. Our objectives were to a) structurally analyze the original items, and b) improve the test by revising the item organization to improve the properties of the SAI-II.

Our initial hypothesis reflected our skepticism that a 1-factor model consistent with the recommended scoring procedure could be identified with 40 items. After extracting various factor solutions using confirmatory and exploratory factor analyses, these solutions yielded mediocre fits that were inconclusive across the attitudinal items, position statements, and total dataset. Exploratory factor analyses on the full dataset found support for a 3-factor solution (Lichtenstein et al., 2008), but fit statistics that compare models by taking into account the degrees of freedom used showed a preference for a 4-factor solution in which the third factor, "understanding of science", split of nicely into "understanding of science" and "science leads to answers". In addition to the theoretical clarity of the 4-factor solution, the small decreases in model error suggested that it provided a parsimonious solution across the 3 SAI-II dataset combinations.

There are several findings in Tables A.9, A.13, and A.17. First, items differed greatly in their factor loadings and many had loadings below the 0.3 cutoff that is appropriate for the sample size. Second, despite using an oblimin rotation to evaluate the item cross loadings, most items presented evidence for some orthogonality in the SAI-II scales, further supporting its intrepretation as a multi-scaled assessment.

We conclude by recommending a 4-factor interpretation of the SAI-II items and offer a revised version in which items with low-loadings were removed and item with poor wording were revised for clarity.

Study 2: SAI-III

The SAI-II represents one of many assessments of scientific interests (Kind, Jones & Barmby, 2007; Kozlow & Nay, 1976; Fraser, 1978; Abd-El-Khalick, Summers, Said, Wang & Culbertson, 2015). However, these measures are all proprietary and many are no longer actively revised or administered. characteristics (Moore & Foy, 1997), scale reliability, and structural properties of a 40-item SAI-II and concluded by recommending a 27-item revision.

Study 2 investigates the structural properties of the initial revision of the SAI-II based on internet administration to a large international sample using the SAPA Project. This study was based on 27 items representing four scales developed Study 1 and as such does not include the deprecated items from the SAI-II . We hypothesized that the factor structure would replicate four distinct but correlated factors. While individual items might demonstrate cross-loadings, their primary loadings would be correspond to the scales developed in Study 1.

Methods

Participants. Our sample consisted of 2,324 adults from 165 different countries during 2013 who completed an online survey at https://sapa-project.org in exchange for customized feedback about their personalities. All data were self-reported. Participants ranged in age from 14 to 90 years (M = 28.85, Median = 26.00, SD = 10.99). Educational attainment levels for the participants are given in Table **??**. Most participants were current university or secondary school students, although a wide range of educational attainment levels were represented. The sample was predominantly US (N = 1393), but drawn from 103 countries. Rank ordered by proportion, participants were 67.7% White, 12.3% Black/African-American, 5.1% Two or more ethnicities, 4.0% Other Hispanic/Latino, 2.6% Mexican/Mexican-American, 1.5% Other, 1.2% Filipino, 1.1% Chinese, 1.1% Puerto Rican, 0.9% Other Asian, 0.8% Indian (Asian) 0.7% Native American, 0.3% Korean, 0.2% Cuban, 0.2% Native Hawaiian, 0.2% Other Pacific Islander, 0.1% Japanese, and 0.1% Alaskan Native. Participants from outside the United States were not prompted for information regarding race/ethnicity.

Measures. The SAI-III constists of 27-items and is organized into 4 scales: Science is Interesting, Science Leads to Answers, Understanding of Science, and Openness to Science A random subset of up to 12-items were administered to participants using the using the Synthetic Aperture Personality Assessment ("SAPA") methodology (Revelle & Laun, 2004; Revelle et al., 2011), a variant of matrix sampling procedures discussed by Lord (1955). With the SAPA procedure, every subject is given a random subset of the total item set. The resulting dataset contain "massive missingess" by design and qualifies as missing completely at random (Graham, 2009, MCAR) as participants respond to as many random items as they wish. As such, the number of total items administered to each participant varied over the course of the sampling period. This resulted in an average of 353 pairwise correlations, which provided high stabilty in the covariance matrix for our structural analysis. Respondents indicated their level of agreement with a statement of a six-level Likert-type response scale: (a) Very Inaccurate, (b) Moderately Inaccurate, (c) Slightly Inaccurate, (d) Slightly Accurate, (e) Moderately Accurate, (f) Very Accurate. The 27-items, hereafter referred to as the SAI-III, is included as Appendix A.45. Administration of these items on the SAPA Project implies the administration of several other scales from the International Personality Item Pool (hereafter IPIP). However, these scales are not discussed until later chapters.

Analyses. The same analyses in study 1 were applied to the pairwise correlation structure applies to the massively missing completely at random SAPA data (i.e., MMCAR).

Results

Table A.33 on page 148 provides descriptive statistics for all 27 items on the SAI-III for the individuals that completed those items in our dataset. Mean values indicate the average item scores (from 1 to 5) and ranged from 1.67 (Item 3812) to 5.20 (Item 3811).

Structural Organization. We performed several exploratory factor analyses with solutions ranging from 1 to 6 factors to a) replicate the structural model from Study 1 with a broader demographic and b) determine the suitability for implementing item response theory with this data. Table A.25 and Figure A.8 present the parallel analysis results that informed the maximum number of factors to explore retaining. The parallel analysis indicated up to 6 factors could be retained, although the break in the scree plot suggests a 4-factor solution is more appropriate. Solutions ranging from 1 through 9 factors were examined using oblimin transformations of the factor loading matrix and are reported in Table A.26 on page 141.

Initially, the factorability of the SAI-III items was examined using the Kaiser-Meyer-Olkin measure of sampling adequacy. The KMO was 0.8, which is considered 'meritorious'. Next, we extracted from 1- to 6-factors using exploratory factor analysis. Revelle's Very Simple Structure minimizes with a 1-factor solution. Velicer's MAP achieves a minimum average partial correlation at both 3- and 4-factors with 0.02, generally agreeing with the intepretation of the scree plot break. The RMSEA did not achieve an acceptable value of <= 0.10 with any of the solutions, but converged at 0.11 after 4-factors were extracted. Last, the BIC achieved a minimum with 6 factors extracted.

Two aid in discerning whether to extract 3- or 4-factors, we conducted exploratory factor analyses and present tables using an oblimin rotation of the items. Comparing the Tables A.27 and A.28 reveals that the large second factor containing high loadings from "The public has no need to understand science" and "Good scientists are willing to alter their ideas based on evidence" splits into two smaller factors which reflect an *understanding of science* and *openness to scientific ideas*. Because the two factor extractions produced two similar and stable factors and the 4-factor extraction split the second factor into 2 cohesive factors, we preferred the 4-factor solution due to a more cohesive theoretical interpretation and replication of the prior study's finding.

The analysis resulted in 4 factors that were consistent with the findings of the previous study. *Interest in science* had high loadings from "I would like to do scientific work" (0.96) and "I would like to be a scientist" (0.93). *Understanding of science* was had medium loadings from items "Scientists must be willing to alter their ideas on the basis of new evidence" (0.70) and "Science requires objective observation of natural events" (0.59). *Science leads to answers* was defined by medium loadings from "Anything we need to know can be found out through science" (0.75) and "Some questions cannot be answered by science" (-0.73). Last, *Openness to science* was defined by medium loadings from "Only highly trained scientists can understand science" (0.67) and "Scientific work is useful only to scientists" (0.62). However, since the items were not explicitly reverse coded in the analysis to see how they naturally form the factor, this factor represents an individuals lack of openness to science and scientific ideas.

Scale Reliability. We calculated reliability measures, such as Omega, on a 4-factor solution. Reliability of the SAI-III improved when compared to the results of the SAI-II in Study 1 (Cronbach's $\alpha = 0.89$, $\omega_{Total} = 0.92$, $\omega_{Hierarchical} = 0.64$). The SAI-III replicates the low general factor saturation, supporting our interpretation of scientific attitudes as a multi-dimensional construct rather than as one concept. For the individual scales, internal consistency was slightly higher for *Interest in Science* ($\omega_{Total} = 0.96$, $\omega_{Hierarchical} = 0.88$), middling for *Openness to Science* ($\omega_{Total} = 0.78$, $\omega_{Hierarchical} = 0.48$), *Science Leads to Answers* ($\omega_{Total} = 0.80$, $\omega_{Hierarchical} = 0.75$), and *Understanding of Science* ($\omega_{Total} = 0.83$, $\omega_{Hierarchical} = 0.66$).

Overall, the reliability of the SAI-III is a slight improvement over the SAI-II.

Item Response Theory Analysis. We used IRT to compare the item information parameters at varying difficulties with the results from Study 1. Item information curves and SAI-III test functions are displayed in Figures A.9 and A.10. Tables A.29, A.30, A.31 and A.32 show the item information parameters in the SAI-III scales. Notably, several revised items loading onto *Interest in Science* displayed higher information values (i.e., $>= 1.0$), which is an improvement over the information values of the original items in the SAI-II. Overall test information was slightly higher for difficulties in the middle of the scale when compared to the SAI-II results in Study 1. Similarly, we found that two items loading onto *Understanding of Science* had information values $>= 1.0$ at various levels of θ (i.e., 3825 & 3826), whereas none of the SAI-II items loading onto that factor provided acceptable scale information. Overall test information for *Understanding of Science* at varying difficulties improves slightly again over the findings from Study 1. While only one item from *Openness to Science* reached an item information value of 1.0 (i.e., 3815), this is an improvement over the scale properties found in Study 1. There, all item information values were below 0.50. The higher item information values yield an overall improvement for the test information, particular in the high difficulties of θ. Last, results for factor *Science Leads to Answers* indicate a similar improvement. Two items (i.e, 3820 & 3821) had information values $>= 1.0$, whereas none of the factor's items on the SAI-II were $>= 0.50$. As a result, test information improves at all difficulties.

2.3. General Discussion

The aim of this set of studies was to use factor analysis and item response theory to examine the structural and item properties of items that measure scientific attitudes. In Study 1, factor analysis of the items drawn from the SAI-II resulted in a four-factor solution: *interest in science*, *openness to science*, whether *science leads to answers*, and an individual's *understanding of science*. Initially, the items in these four factors suffered from low-loadings and provided low information at varying scale difficulties.

When compared to previous intepretations of the SAI-II by Lichtenstein et al. (2008), the factor structure discovered here is very similar, but we preferred a four-factor solution which differentiated items that described the degree to which an individual understands science as a discipline and process, vs. the degree to which they believe science leads to answers to questions about the natural world. Possible explanations for this descrepancy are differences in sample size and sample demographics.

Unlike previous research, this is the first study to revise the items and replicate the structural properties of the SAI-II using an online sample that displayed broad demographic characteristics. Taken together, the two studies extend previous research by Lichtenstein et al. (2008) and represent a thorough psychometric investigations of the SAI-II and SAI-II as they apply to both psychologists and science educators. As such, they help address confusion over the structural interpretation of the SAI-II and its usability with adult populations. In nearly all cases, the SAI-III displayed better item and scale properties despite being composed of fewer items.

Despite the fact that this is a thorough investigation of scientific attitudes, this study as limitations. First, we did not include items from *all* available assessments of scientific attitudes. Including more items may alter the interpreted structure of scientific attitudes or provide an understanding of the lower-order structure of each scale of the SAI-II and SAI-III. Second, the factor structure was produced in both studies by self-report. There is a risk that participants were responding based on socially desirability, whereby it may be unpopular to explicitly reject science.

In conclusion, studies 1 and 2 help provide a clearer understanding of the facets that make up and individuals attitudes about science and provide a conceptual framework to facilitate the development of future items and revisions to assess scientific attitudes

CHAPTER 3

Demonstrating the convergent validity of the SAI-III using temperament, ability, and interests.

3.1. Introduction

In order to provide researchers with a framework to understand how individuals think about science as a discipline, scientific ideas, and scientific authority, Chapter 2 assessed the factor structure of individuals' scientific attitudes. The Scientific Attitudes Inventory - Revised (SAI-II), a 40-item revision of the original Scientific Attitudes Inventory, is a widely used assessement for measuring the scientific attitudes of individuals (Moore & Foy, 1997; Moore & Sutman, 1970). This inventory served as the basis for the revision recommended in Chapter 2, the SAI-III. However, in order for the inventory to be useful we must establish its construct validity to faciliate wider usage. We begin by examining previous literature for associations in non-cognitive personailty traits, cognitive ability, and vocational interests.

Personality traits provide an initial framework for exploring differences in scientific attitudes. Many factors influence who become interested in science and why, including need for cognition and individual differences in personality traits (Feist, 2006). As such, high levels of specific personality traits may make it easier for some individuals to become interested in science as a career choice. For example, individuals that have a high interest in science are typically higher on conscietiousness, openness to experience, and introversion (Charyton & Snelbecker, 2007; Feist & Gorman, 1998). A study on college students predicted levels of interest in science using personality dimensions (Feist, 2012). Feist compared college undergraduates on personality dimensions of openness to experience, conscientiousness, and introversion as well as *need for cognition*, a cognitive style associated with openness to experience. He concluded that personality relates to students' scientific attitudes and interests. Specifically, openness to experience, introversion, and conscientiousness were all correlated with scientific interests. Additional work by Feist (2013, 2010) offers a conceptual framework that defines how individual differences in personality make interest and talent in science more likely. These individual differences yield important differences in a) cognitive traits, b) social traits, c) affective traits, and d) clinical traits. When these factors interact they can increase the propensity that an individual will engage in scientific thought or operate in a manner consistent with a natural-scientific worldview. Additionally, a meta-analysis by Feist (1998) found large effect sizes for the positive and negative poles of *conscientiousness.* Overall, individual differences in personality traits provides a promising area to investigate associations with the SAI-III.

Cognitive ability provides the second framework used to establish the concurrent validity of the SAI-II. There is substantive evidence to support the association between cognitive ability and scientific interests, whether at the level of college major, vocation or achievement (Lubinski et al., 2006, 2001). Two studies on a longitudinal cohort looked at accomplishment in science, technology, education, and math (i.e., STEM) (Wai et al., 2010). The sample was initially comprised of precocious 13-year-olds who had scored greater or equal to 500 on the SAT - Quantitative (on an 800-point scale). Not only did the gifted students pursue STEM majors and vocations at greater rates than their normative peers, but among the gifted students, those who engaged in more pre-college STEM education were more likely to pursue STEM majors and careers, suggesting an interaction between intelligence and interests. However, one question for future research is to consider how the opportunities given to participants in such a selective sample may have influenced their interest in science. Similarly, recent evidence suggests that cognitive ability plays a role in the number of accomplishments garnered. A follow-up study on the same sample of precocious 13-year-olds concluded that they were more likely to choose prestigious occupations and be employed by impressive institutions at age 38 than graduate students at prestigious universities (Kell et al., 2013). For example, more than 7% of the sample received tenure at research-intensive universities. Taken together, cognitive ability is important not only in the pursuit of a STEM education and vocation but also for success within that vocation as measured by the number of accomplishements.

However, spatial ability is another important source of individual differences that has been historically neglected until recently (Cheng & Mix, 2014; Mix & Cheng, 2012; Kell et al., 2013). A review of 50-years of longitudinal research highlighted the role of spatial ability in STEM education, pointing out that individual differences in spatial ability can help inform known aptitude by treatment interactions (Lubinski, 2010). Specifically. Lubinski argues that spatial ability is crucial for talent identification and that selecting STEM students without considering spatial ability may be pointless. Another longitudinal study of the same precocious 13-year-olds investigated whether spatial ability differentially predicted successfully holding a patent or refereed publication, over and above the SAT math and verbal subtests (Kell et al., 2013; Kell & Lubinski, 2013). While SAT math accounted for 10.8% of the variance, spatial ability accounted for an additional 7% of the variance. The authors conclude that spatial ability plays a unique role in measured creativity, over and above the typically measured abilities.

Last, vocational interests also reflect important individual differences that relate to scientific attitudes. Vocational interests are preferences for specific activites, such as science, that can motiviate individuals toward certain environments (Rounds, 1995; Su, Rounds & Armstrong, 2009). These dispositional traits determine not only what occupations interest individuals, but also their level of acheivement in those fields (Rounds & Su, 2014). Additionally, they're capable of predicting outcomes, such as who goes into a scientific vocation, over and above personality traits and cognitive ability (Stoll, Rieger, Lüdtke, Nagengast, Trautwein & Roberts, 2017). This research therefore considers vocational interests alongside personality traits and cognitive ability in examining individual differences in attitudes about science.

The aim of the present study was to establish the convergent and concurrent validity of the SAI-III as a measure of scientific attitudes and interest in several ways. The following research questions guided our analyses: First, do individuals high in scientific interest have different personality traits consistent with previous research by Feist and colleagues? We expect to find that Interest in Science correlates positively with conscientiousness, openness to experience, and negatively with extraversion. Second, will people more interested in science have a greater desire to go into a scientific career? Here we expect to find a positive correlation between scientific interest and the *Analysis* scale of the Oregon Vocational Interest Scales (Pozzebon et al., 2010). Last, consistent with work by Lubinski et al. (2006, 2001); Wai et al. (2010), is higher cognitive ability associated with an increased interest in and understanding of science? We expect to find a positive correlation between scientific interest and scientific understanding and various facets of cognitive ability.

3.2. Methods

Participants

Our sample was identical to that of Study 2 in Chapter 2. It consisted of 2324 adults from 165 different countries during 2013 who completed an online survey at https://sapa-project.org in exchange for customized feedback about their personalities. All data were self-reported. Participants ranged in age from 14 to 90 years (M = 28.85, Median = 26.00, SD = 10.99). Most participants were current university or secondary school students, although a wide range of educational attainment levels were represented. The sample was predominantly US (N = 1393), but drawn from 103 countries. Rank ordered by proportion, participants were 67.7% White, 12.3% Black/African-American, 5.1% Two or more ethnicities, 4.0% Other Hispanic/Latino, 2.6% Mexican/Mexican-American, 1.5% Other, 1.2% Filipino, 1.1% Chinese, 1.1% Puerto Rican, 0.9% Other Asian, 0.8% Indian (Asian) 0.7% Native American, 0.3% Korean, 0.2% Cuban, 0.2% Native Hawaiian, 0.2% Other Pacific Islander, 0.1% Japanese, and 0.1% Alaskan Native. Participants from outside the United States were not prompted for information regarding race/ethnicity.

Measures

All measures were administered using the Synthetic Aperture Personality Assessment ("SAPA") methodology (Revelle & Laun, 2004; Revelle et al., 2011), a variant of matrix sampling procedures discussed by Lord (1955). With the SAPA procedure, every subject is given a random subset of the total item pool. As such, the number of total items administered to each participant varied over the course of the sampling period. This is different from many online test frameworks, in which all participants receive an identical set of items. This difference allows SAPA researchers to identify pairwise correlations across all items that consist of inventories for ability, personality, and interests. Using the SAPA procedure, our study resulted in an average of 353 pairwise correlations.

With the exception of the SAI-III and ICAR60, all of the temperament and interest items administered were from the International Personality Item Pool (IPIP; http://ipip.ori.org/), a repository for public domain personality items and inventories (Goldberg, Johnson, Eber, Hogan, Ashton, Cloninger & Gough, 2006). We assessed participants on these items using a Likert-like scale. Respondents indicated their level of agreement with a statement of a six-level Likert-like response scale: (a) Very Inaccurate, (b) Moderately Inaccurate, (c) Slightly Inaccurate, (d) Slightly Accurate, (e) Moderately Accurate, (f) Very Accurate. The first measure used was measure of personailty traits was the IPIP-NEO, a 100-item IPIP inventory based on the NEO-PI-R (Costa Jr & McCrae, 1992). These scales consist of agreeableness, conscientiousness, emotional stability, extraversion, and intellect and are further divided into facets that load onto the main factors. On average, participants took 17 items. The second was the Big Five Aspects Scales (DeYoung et al., 2007). On average, participants took 19 items. The Oregon Vocational Interest Scales was used to measure interests, which is a public domain self-report measure of vocational interests by Pozzebon et al. (2010) that consists of 92 items. Vocational interests are divided into eight scales: *a*) leadership, *b*) organization, *c*) altruism, *d*) creativity, *e*) analysis, *f*) producing, *g*) adventuring, and *h*) erudition. For each item, participants rated their level of interest in each occupational description (e.g., Care for sick people). On average, participants took 27 items.

Scientific interest and attitude items were randomly sampled from the SAI-III. The SAI-III consists of 27-items and is organized into 4 scales: Science is interesting, Science leads to answers, Understanding of science, and Openness to science A random subset of up to 12-items were administered to participants. The 27-items, hereafter referred to as the SAI-III, is included as Appendix A.45.

To measure ability, participants were given four item types from the International Cognitive Ability Resource (i.e., ICAR). The total ICAR set which includes: Letter and Number Series items, Matrix Reasoning items, Verbal Reasoning items and Three-dimensional Rotation items (Condon & Revelle, 2014). Letter and Number Series items prompt participants with short digit or letter sequences and ask them to identify the next position in the sequence from among six choices. Matrix Reasoning items display 3 × 3 arrays of geometric shapes with one of the nine shapes missing. Participants are instructed to identify which of the six geometric shapes presented as response choices will best complete the stimuli. The Verbal Reasoning items include logic, vocabulary and general knowledge questions. The Three-dimensional Rotation items present participants with cube renderings and ask participants to identify which of the response choices is a possible rotation of the target stimuli.

3.3. Results

Individual trait, interest, and ability scores in the SAPA sample were calculated using the average of the observed items, which differed by participant. Analyses were performed using the *psych* package (Revelle, 2018) in the *R* statistical programming language (R Core Team, 2018).

Descriptive statistics for the SAPA sample are provided in Table A.33 on page 148. As shown in Table A.34 on page 149, personality traits derived from the NEO-PI-R relate to the scales of the SAI-III. Consistent with some of our predictions of our first hypothesis, these data show that *Interest in Science* has a small but stable correlation with *Intellect* ($r = 0.19, p < .001$). However, significant correlations were not observed for the NEO-PI-R traits of Conscientiousness ($r = -0.01, p = n.s.$) and Extraversion ($r = -0.02, p = n.s.$). Additionally, a small, positive correlation was observed between *Understanding of Science*, an additional scale of the SAI-III, and *Intellect* ($r = 0.18, p < .001$).

Also consistent with our predictions, there was a small, positive correlation between the *Interest in Science* scale and the *Intellect* scale ($r = 0.18, p < .001$) on the Big Five Aspects Scales (hereafter BFA). Additional positive correlations were observed between *Understanding of Science* and both of the *Intellect* ($r = 0.15, p < .001$) and *Openness* ($r = 0.10, p < .001$) scales of the BFA. Taken together, the findings of the small, positive correlations between two scales of scientific attitudes and the Openness/Intellect traits provide support for the validity of the SAI-III.

Our second hypothesis stated that scientific attitudes would be positively associated with the Analysis scale of the ORVIS. Consistent with our predictions, a strong, positive correlation was found with *Interest in Science* ($r = 0.52, p < .001$), as well as moderate correlations for *Science Leads to Answers* ($r = 0.17, p < .001$) and *Understanding of Science* ($r = 0.29, p < .001$) (see Table A.36). Additional moderate correlations were observed between *Interest in Science* and *Erudition* ($r = 0.20, p < .001$) as well as *Production* ($r = 0.22, p < .001$). These results provide support for the validity of the *Interest in Science* and *Understanding of Science* scales in predicting interest in a career involving analysis, such as science.

Last, our third hypothesis stated that scientific attitudes would be positively associated with cognitive ability. Results presented in Table A.37 on page 152 were consistent with our predictions. *Interest in Science* was positvely associated with the all administered scales of the

ICAR cognitive ability test ($r = 0.23, p < .001$), including the Letter and Number Series ($r = 0.17, p < .001$), Matrix Reasoning ($r = 0.14, p < .001$), 3D Rotation ($r = 0.18, p < .001$), and Verbal Reasoning ($r = 0.17, p < .001$). Additionally, small, positive correlations were found between *Understanding of Science* and the ICAR ($r = 0.22, p < .001$), Letter and Number Series ($r = 0.18, p < .001$), Matrix Reasoning ($r = 0.10, p < .001$), 3D Rotation ($r = 0.14, p < .001$), and Verbal Reasoning ($r = 0.18, p < .001$). These results replicate previous findings between cognitive ability and scientific interest and provide additional convergent validty for the SAI-III scales.

3.3.1. Incremental Validity

Logistic regression models were used to evaluate the incremental validity of the SAI-III scales in predicting participation in STEM majors over and above traits, abilities, and interests. The SAPA Project collects data on participant's college majors and the disciplines of those majors. The discipline options include: Undecided, Arts, Business, Communications, Community and Social Services, Education, Engineering and Technology, Language and Literature, Mathematics, Medicine and Allied Health, Natural Sciences, and Social Sciences. For this analysis, a dichotomous variable was coded as 1 based on the selection of one of the following majors: Computer and Information Systems, Engineering and Technology, Mathematics, Natural Sciences, and Social Sciences.

The first analysis regressed the dichotomous STEM variable onto a) NEO-PI-R Intellect, b) the ICAR 60 Score, and participant's c) ORVIS Analysis score based on the correlational findings. Results are reported in Table A.38 on page 153. The analysis was significant ($\chi^2(3) = 77.27, p < .001$), and two variables were found to be significant predicts of having a STEM major after controlling for other variables: ORVIS Analysis ($\chi^2(1) = 53.51, p < .001$) and the ICAR 60 Total Score ($\chi^2(1) = 19.94, p < .001$). The Intellect scale of the IPIP's public domain NEO-PI-R was only marginally significant ($\chi^2(1) = 3.82, p = .051$).

A second analysis regressed particpant's STEM major score onto the previous variables in addition to the four scales of the SAI-III: a) Interest in Science, b) Openness to Science, c) Understanding of Science, and d) Science Leads to Answers. Results are displayed in Table A.39. The overall model was significant ($\chi^2(4) = 90.33, p < .001$), with three significant predictors: ORVIS Analysis ($\chi^2(1) = 53.51, p < .001$), ICAR 60 Total Score ($\chi^2(1) = 19.94, p < .001$), as well as Interest in Science ($\chi^2(1) = 10.17, p = .001$). Additionally, both Intellect ($\chi^2(1) = 3.82, p = .051$) and Understanding of Science ($\chi^2(1) = 2.83, p = .09$) were marginally significant. Last, the Wald χ^2 test was used to compare the two models in order to demonstrate incremental validity of the SAI-III scales in predicting STEM majors. Results indicated that the augmented model was a significant improvement over the base model with traits, ability, and interests ($\chi^2(4) = 13.06, p = .011$).

These results suggest that the SAI-III scales, although correlated, are conceptually different from existing items that are drawn from current conceptualizations of personality traits, abilities, and interests and support the incremental validity of the SAI-III scales.

3.4. Discussion

The results of the present study provide support for the convergent, concurrent and incremental validity of the SAI-III as a measure of scientific attitudes and interests. As expected, the SAI-III was positively related to Openness to Experience, including the Intellect facet. The magnitude of the correlations for the SAI-III revision was small but stable. The SAI-III taps into

4 facets of scientific attitudes, two of which appear to be related to an individual differences in personality traits and provide additional information about who is interested in science and understands science as a discipline over and above differences in personality traits.

Although the strength of the correlations between 3 of the SAI-III scales and the Analysis vocational interest of the ORVIS suggest that the two are closely related, the additional correlations with Erudition and Production suggest that the SAI-III taps into a broader conceptualization of scientific interest that just the analysis component to scientific vocations, including an interest in scholarly activities and producing novel things.

The finding that 3 scales of the SAI-III are positively correlated with cognitive ability is encouraging in that it is consistent with previous research suggesting that cognitive ability is important for providing access to certain interests and vocational outcomes (Reeve & Heggestad, 2004; Hunter, 1986; Judge, Higgins, Thoresen & Barrick, 1999; Roberts, Kuncel, Shiner, Caspi & Goldberg, 2007), and that all aspects of cognitive ability can faciliate an interest in science. It may be that while personality traits and motivational interests can predict who's interested in science and goes into scientific majors, that cognitive ability differentially predicts who succeeds in those college majors and obtains success in a scientific career. In this way, traits, abilities, and interests may be associated with different aspects of the SAI-III and the strength of those associations may change across the lifespan.

Although the present study provides encouraging results, this evidence must be regarded as preliminary until the SAI-III can be shown to predict STEM majors and STEM vocations. A future investigation should seek to evaluate the incremental validity of the SAI-III in predicting these outcomes over and above existing measures of personality traits, cognitive ability, and vocational interests.

CHAPTER 4

Replicating the association of scientific attitudes with trait, abilities, and interests using Project TALENT

Project TALENT is a national longitudinal study that surveyed high-school students beginning in 1960. It investigated students' interests, career plans, temperament, and life objectives (Wise & McLaughlin, 1977). It was designed to be representative of the US population and sampled across economic, cultural, social, and urban backgrounds. Roughly 440,000 students from across the country participated, or 5% of the population, or which 377,000 cases are available. By design, it investigates why some students learn and others not. While Chapters 2 and 3 are assess the concurrent and construct validity of the scientific attitudes using the SAI-III, their associations with traits, abilities, and interests must be replicated in an independent sample. The purpose of Study 3 is to replicate the associations of scientific attitudes with temperament, ability, and interests using Project TALENT. In doing so, it further establishes that a proper conceptual framework of scientific attitudes and interests must draw collectively from literature on temperament, abilities, and interests.

Project TALENT has been widely used to investigate associations between personality and ability. The relationship between intelligence and personality traits in the dataset were established in a study by Reeve, Meyer & Bonaccio (2006) by examining the correlations between several personality and ability scales. The authors repeated their analyses using latent modeling techniuqes in order to separate the variances due to different domains of cognitive ability and conclude with a range of associations.

Recent work by Major, Johnson & Deary (2014) also investigated the relations of personality traits to intelligence using a series of quadratic and generalized additive models (i.e., GAMs). Their work found support for modeling traits and abilities using non-linear associations when possible. Their results found evidence for associations with personality and intelligence, particular when latent scoring techniques were used in place of participant's observed scale scores, where important effect sizes may not be found.

Project TALENT is also a rich source of demographic and familial data. A study by Damian & Roberts (2015b) examining the associations of birth order with personality and intelligence estimated the links between birth order and outcomes in several social categories and personality traits. The authors concluded with evidence that birth order may relate to both personality and intelligence. In addition to birth order effects, the longitudinal design of the study makes it possible to investigate outcomes. Research investigating occupational attainment classified participants into 12 categories based on their response patterns for ability and interest scales. The findings suggest that abilities and interests interact with gender and socioeconomic status to predict occupational attainment.

Project TALENT's measures of temperament, different types of abilities, and interests allows researchers to investigate the associations in a manner similar to the SAPA dataset. Despite the previous research on temperament and ability using Project TALENT, to our knowledge were are the first to examine the relation of scientific attitudes to temperament and cognitive ability. Chapter 4 attempts to replicate the correlational findings from Chapter 3 in order to argue that an interpretation of scientific attitudes is only meaningful when the conceptual framework includes measures of temperament and ability, two commonly studies domains of differential psychology. Chapter 3 found that Intellect related to two scales of the SAI-III, Understanding Science and Interest in Science. We first hypothesize that the Project TALENT temperament scales that are conceptually similar to the NEO-PI-R Intellect scale will correlate with scientific attitudes, interests, and domain knowledge. Second, Chapter 3 found moderate effects for all cognitive ability scales administered as part of the ICAR Project. We hypothesize that cognitive abilities will positively correlate with scientific attitudes and interests. In sum, this study seeks to replicate the findings of Chapter 3 in support of an integrated understanding of scientific attitudes using a large representative sample.

4.1. Methods

4.1.1. Participants

Project TALENT is a national longitudinal study of 440,000 representative American high-school students (Wise & McLaughlin, 1977). Follow-up data was collected at 1, 5, and 11-years after high-school graduation, however the present study only used the data from the base year. Questionnairres were administered that assess cognitive skills, collected demographic information, extracurricular and vocational interests, temperament, and academic performance. Project TALENT is unique in that it combines measures of aptitude, cognition, social life, and psychological traits and is therefore able to be used for lifespan hypotheses.

4.1.2. Measures

The Project Talent Personality Inventory (PTPI) included 150 items from which ten different scale composites. The scales include: a) Vigor (i.e., the average physica activity), b) Calmness (i.e., the ability to remain calm in emotional situations), c) Mature Personality (i.e., the ability to accept assigned responsibility), d) Impulsiveness (i.e., the tendency to make quick decisions), e) Self-Confidence (i.e., the willingness to act independently), f) Culture (i.e., displaying refinement and good taste), g) Sociability (i.e., the degree to which one enjoys being around people), h) Social Sensitivity (i.e., the ability to consider the other persons thoughts and situation), i) Tidiness (i.e., the desire for order), and j) Leadership (i.e., the degree to which one seeks out responsiblity) (Damian & Roberts, 2015b; Wise & McLaughlin, 1977). Participants responded to the items using a 5-point Likert scale, ranging from "Not Very Well" to "Extremely Well". As item data are not available in the base year dataset, we relied on the scale scores computed by the Project TALENT staff and provided by the American Institutes of Research. However, in order to make our work comparable to previous chapters, we rely on work by Pozzebon, Damian, Hill, Lin, Lapham & Roberts (2013); Reeve et al. (2006) which established the validity of the PTPI and mapped its scales onto Big Five conceptualizations of personality traits. The mappings between the IPIP NEO-PI-R and the Project TALENT scales are as follows: Agreeableness corresponds to Social Sensitivity, Extraversion corresponds to Sociability, Leadership, Impulsivity, Vigor, and Self-confidence, Emotional Stabiity corresponds to Calmness, Conscientiousness correponds to Tidiness and Maturity, and Openness correponds to Culture.

Additionally, Project TALENT contains scales that represent different domains of cognitive ability. These domains include verbal, quantitative, and visualization and spatial abilities.

These tests included: Vocabulary (30-items), Information (365-items), Memory for Sentences (16-items), Memory for Words (24-items), Disguised Words (30-items), English Total (113-items), Word Functions in Sentences (24-items), Reading Comprehension (48-items), Creativity (20-items), Mechanical Reasoning (20-items), Abstract Reasoning (15-items), Visualization in Two Dimensions (24-items), Visualization in Three Dimensions (16-items), Arithmetic Reasoning (16-items), High School Math (24-items), and Advanced Math (16-items). In order to extract a g component to allow for comparisons to the correlational findings from Chapter 3, an Exploratory Factor Analysis using Maximum Likelihood was performed and the first unrotated factor score was saved for each participant ($\chi^2(104) = 1,597,463, p < .001, TLI = 0.81, RMSEA = 0.20$). This factor had an eigenvalue of 11.64 and accounted for 73% of the total variance.

Project TALENT also included several scales to measure attitudes and interests. Of the relevant scales, the following measure domain knowledge: Physical Science, Biological Science, and Scientific Attitudes. Collectively, these domains may be similar to the Understanding of Science scale on the SAI-III. Additional measures were included, such as "How many semesters of science courses" the participant had taken as an indicator for interest in science.

4.1.3. Analyses

All analyses were conducted in R (R Core Team, 2018) using the `psych package` (Revelle, 2018). Pearson correlations were used to investigate associations between scales, as only the scale level data were available. Additionally, maximum likelihood was used to extract latent factors as the Project TALENT dataset had a larger sample size, resulting in more stable correlation matrices as well as normally distributed scales of interests.

4.2. Results

Descriptive statistics for the Project TALENT scales are available in Table A.42.

4.2.1. Structural Analysis of Ability

In order to replicate findings from Chapter 3, a general factor of intelligence had to be extracted from the Project TALENT ability scales, replicating analyses by Damian & Roberts (2015b). Descriptive statistics for the ability scales are available in Table A.40 on page 155. Exploratory factor analysis was fit in order to extract latent scores for participants ($\chi^2(104) = 1,597,463, p < .001, TLI = 0.81, RMSEA = 0.20.$).

Results are displayed in Table A.41 on page 156, in which all but 3 items had loadings $>= 0.50$. These findings support the extraction of a general cognitive ability factor to support later analysis. Following this, reliability statistics were also calculated for the scales that comprise the general cognitive ability factor and found to be satisfactory ($\alpha = 0.91, \omega_{Hierarchical} = 0.68, \omega_{Total} = 0.93$)).

Our first hypothesis stated that we would replicate the association between Openness to Experience/Intellect and Scientific Attitudes found in Chapter 3. Table A.43 contains results consistent with some of our predictions. Due to the sample size, all reported correlations are significant. The data show that *Scientific Attitude* has a moderate correlation with *Culture* (Openness; $r = 0.14, p < .001$). However, this unlike the results from Chapter 3, this association was not the greatest in magnitude. Significant moderate correlations were also observed for *Social Sensitivity* (Agreeableness; $r = 0.17, p < .001$), *Calmness* (Emotional Stability; $r = 0.15, p < .001$), *Vigor* (Extraversion; $r = 0.13, p < .001$), *Self-confidence* (Extraversion; $r = 0.15, p < .001$), and *Mature Personality* (Conscientiousness; $r = 0.14, p < .001$).

Additionally, domain knowledge in *Physical Science* was moderately associated with *Vigor* ($r = 0.13, p < .001$), *Calmness* ($r = 0.15, p < .001$), *Self-confidence* ($r = 0.14, p < .001$), and *Mature Personality* ($r = 0.17, p < .001$). Similar correlational patterns were observed between *Biological Science* and *Social Sensitivity* ($r = 0.10, p < .001$), *Vigor* ($r = 0.13, p < .001$), *Calmness* ($r = 0.15, p < .001$), *Self-confidence* ($r = 0.14, p < .001$), and *Mature Personality* ($r = 0.17, p < .001$).

Table A.44 on page 159 shows correlations between participant's general cognitive ability factor analytic scores (which represented *g*) and scientific attitudes and domain expertise were computed to test predictions from hypothesis 2. Consistent with our second hypothesis, cognitive ability was significantly associated with *Physical Science Knowledge* ($r = 0.09, p < .001$), *Biological Science Knowledge* ($r = 0.08, p < .001$), *Scientific Attitudes* ($r = 0.08, p < .001$), as well as the *Number of Science Courses* taken by the participant ($r = 0.06, p < .001$). However, the effect sizes for the number of science courses taken are much smaller than those observed with Interest in Science in previous chapters as well as those measuring physical and biological domain knowledge when compared with Understanding of Science.

4.3. Discussion

We investigated the relations between traits, cognitive ability, and scientific attitudes using the Project TALENT dataset based on results in Chapter 3 which found evidence that scientific attitudes were moderately correlated with temperament traits such as openness to experience, as well as all facets of cognitive ability as measured by the International Cognitive Ability Resource.

Overall, this chapter improved upon previous work by replicating the interactions between traits, abilities, and scientific attitudes in a large representative sample of U.S. high school students. However, some of the results differ from findings in Chapter 3. Openness to Experience appears not be the aspect of temperament with the greatest magnitude of association. In fact, Agreeableness, Extraversion, and Conscientiousness had higher Pearson correlations, contradicting results from Chapter 3. One reason for this difference could be that the individual items that comprise the culture scale are more closely related to the Artistic facet of the NEO-PI-R's Openness trait, instead of the Intellect facet (Reeve et al., 2006). For example, this scale contains items such as "I enjoy beautiful things" and "I think culture is more important than wealth." This limitation is expected due to the lack of items that correspond to a modern conceptualization of Openness-Intellect.

Additionally, the effect sizes between cognitive ability and scientific attitudes and domain expertise were generally smaller than found in Chapter 3. To the extent that these effect sizes are accurate, cognitive ability may play a smaller role for high school student's scientific attitudes than the large, adult sample collected by the SAPA Project. This finding should be an important consideration for measuring and analyzing scientific attitudes across different populations. A follow-up study should investigate whether this association shows invariance across the different collection times using the longitudinal dataset.

In conclusion, it was determined that the Project TALENT's scientific attitudes scales are positively correlated with aspects of temperament and ability. Although the magnitude of the effect sizes differs from previous studies, this work supports the argument that future research on scientific attitudes and interests should carefully consider the concurrent measurement on traits, cognitive ability, and interests in order to be conceptually complete.

CHAPTER 5

Integrating Scientific Attitudes with Temperament, Abilities, and Interests

In the first chapter, I outlined a framework using differential psychology for thinking about who becomes interested in science and why. Despite this scientific interest being of interest to researchers for over 100 years, there existed little consensus regarding how to measure scientific attitudes and how to best investigate them into differential psychology. Many of the available assessments for investigating differences in scientific attitudes failed to incorporate literature on individual differences and had not survived psychometric evaluation. As such, this research proposed the development of a new conceptual framework using temperament, cognitive ability, and motivational interests for validation.

Perhaps the main challenge for integrating research on scientific interests into differential and cognitive psychology has been the lack of a validated assessment that's grounded in modern theoretical approaches and supported by psychometric evaluations. A multitude of tests proported to measure very different facets of scientific interests. Worse, many of these assessments were designed theoretically using qualitative research without being psychometrically validated against appropriate populations in order to encourage researchers to use those assessments. While item development and revision should be a continuing process, many of the challenges with measuring scientific attitudes were addressed in this body of work, validating a theoretical structure for designing items to measure scientific attitudes against two separate populations in Chapter 2. Demographically, the adult samples provide sufficient range and variability in participant gender, ethnicity, and education and collectively encourage the use of the SAI-II and SAI-III with adult samples. Additionally, the revision and removal of many SAI-II items helps establish a shorter form test with improved psychometric properties. As such, Chapter 2 concludes with a validated, short form assessment of scientific attitudes and interests and provides scale information across a sufficiently large and diverse sample. These scales assess *Interest in Science*, *Understanding of Science*, the degree to which a participant believes that *Science Leads to Answers*, and one's *Openness to Science*.

However, interests are guided by individual differences in temperament and enabled by abilities. Chapters 3 and 4 integrated the measurement of scientific attitudes with modern conceptualizations of temperament (e.g., Big 5 and NEO-PI-R) as well as domains of cognitive ability (e.g., International Cognitive Ability Resource). The ultimate goal of this work was to demonstrate that discussion and measurement of scientific attitudes should include measurement of temperament, ability and interests in order to refine our understanding of how these domains interact to predict important life outcomes, such as college major or chosen occupation. While researchers can administer the SAI-III by itself, joint administration allows for further refinement of the proposed framework and validation of the SAI-III scales.

Collectively, the chapters in this work establish an improved measure of scientific attitudes and demonstrate concurrent and incremental validity with temperament, ability, interests, and outcomes. However, several limitations should inform future work. First, this work only establishes the concurrent validity with outcomes, such as major. A longitudinal sample in which the SAI-III is administered before college major or occupation is chosen would help assess the predictive validity of the SAI-III in important life outcomes. Similarly, many questions remain unanswered about the differences in associations between Chapters 3 and 4. The chapters were defined by important sample differences that raise questions about scientific attitudes. Differences in age indicate that scientific attitudes may be guided by temperament in childhood and ability in adulthood. Chapter 3 used a large, online sample from the United States that consisted of adults. However, work in Chapter 4 used a nationally representative sample of high-school students. Additionally, cohort differences raise important questions about how differences in the political landscape between the 1960s and 2010s may have changed how individuals think about science. Further work should investigate whether ability plays a larger role in predicting scientific attitudes later in life than temperament, or if these observed differences are due to cohort effects. Last, due to sample size we were unable to investigate whether our scales were invariant across genders. Additional work should investigate whether there are gender differences in the observed psychometric structure of the SAI-III scales as well as the scale assocations with TAI.

It is time to move the study of attitudes about science forward, across disciplines, and integrate future research using frameworks of different psychology. In doing so, scientific attitudes aid the aforementioned domains by providing predictive utility in examining how attitudes develop during formative school years, evaluating differences in choices for college majors, examining which STEM major participants continue into STEM occupations, and which types of individual achieve in STEM fields. In sum, this work proposes a framework for understanding the development of scientific attitudes and addresses the lack of a validated assessment. The four scales outlined in the SAI-III can serve as a basis for future research. Future research should continue with the development and validation of novel items, use its scales to assess school intervention programs, and conduct longitudinal research on the development of attitudes over time.

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APPENDIX A

SAI-III

List of Figures

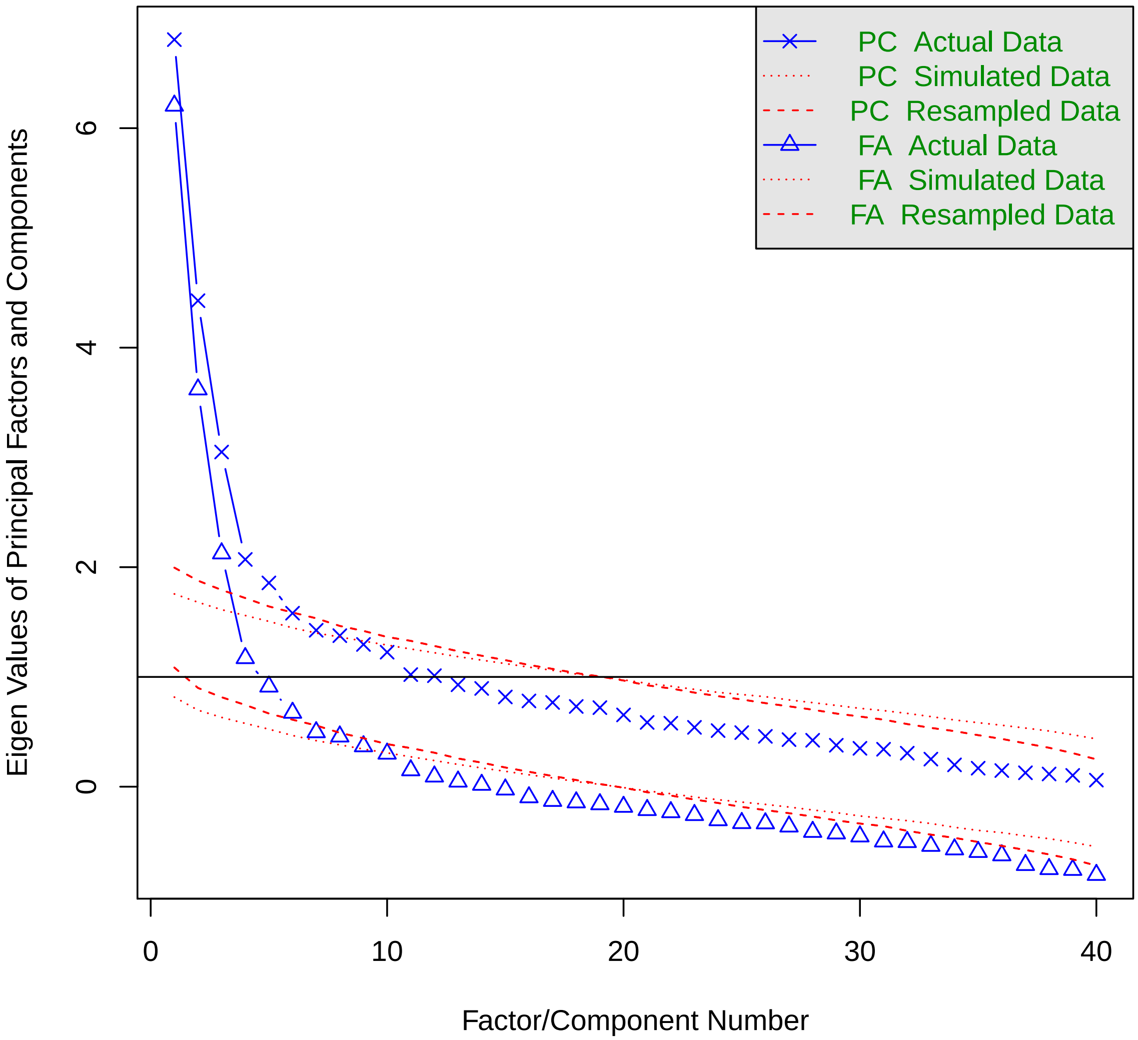


Figure A.1. SAI-II Parallel Analysis and Scree Plot for Attitude Items. The top pair of red lines represent principal components from random data. The bottom pair of red lines reflect the eigen values from the factor analysis of random data. The blue lines reflect the actual results.

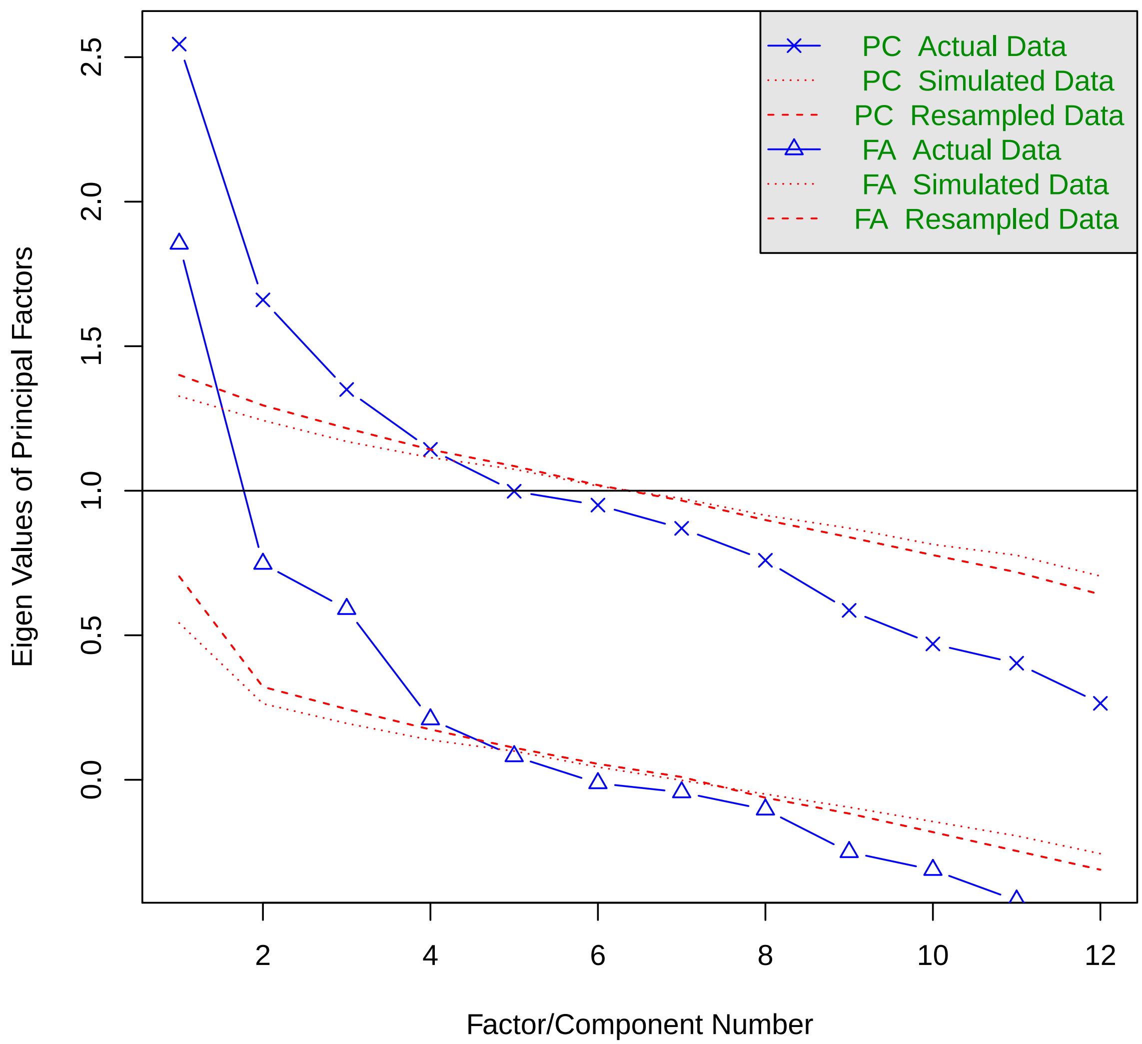


Figure A.2. SAI-II Parallel Analysis and Scree Plot for Position Statements.

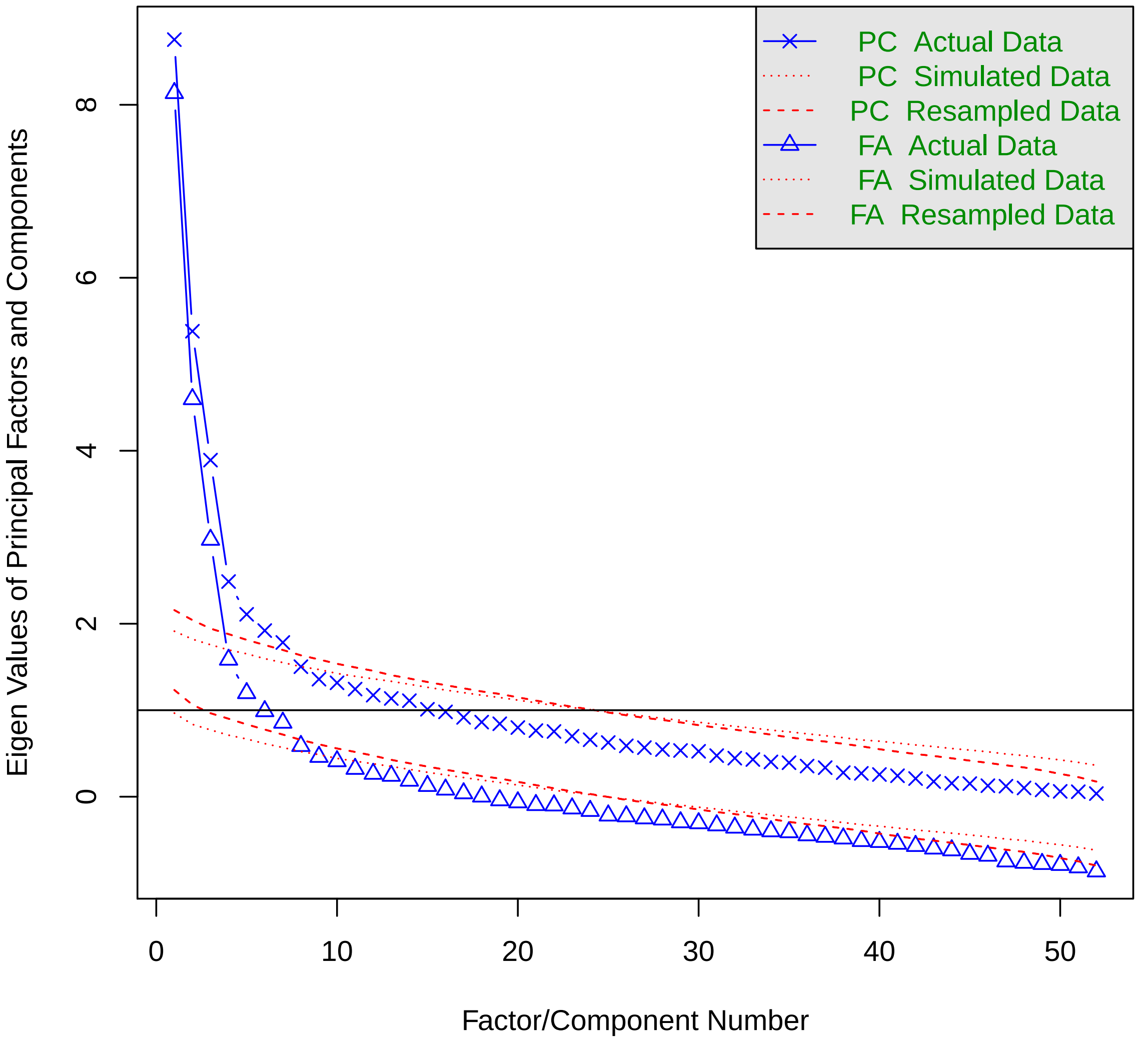


Figure A.3. SAI-II Parallel Analysis and Scree Plot for All Items. The top pair of red lines represent principal components from random data. The bottom pair of red lines reflect the eigen values from the factor analysis of random data. The blue lines reflect the actual results.

Figure A.4. EFA: 4-factor solution.

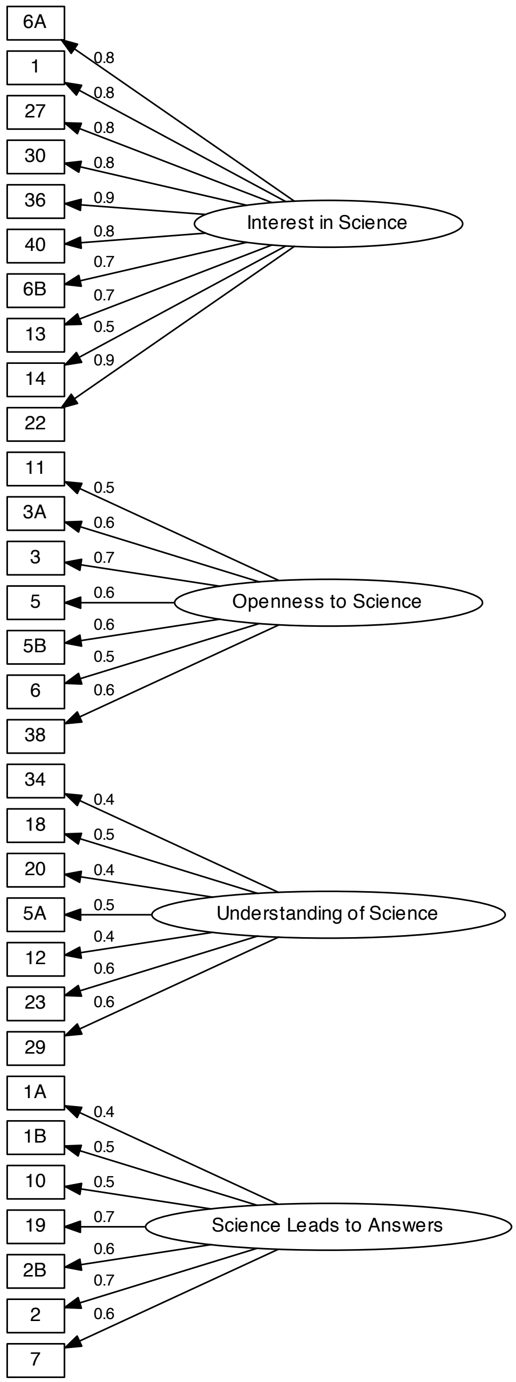
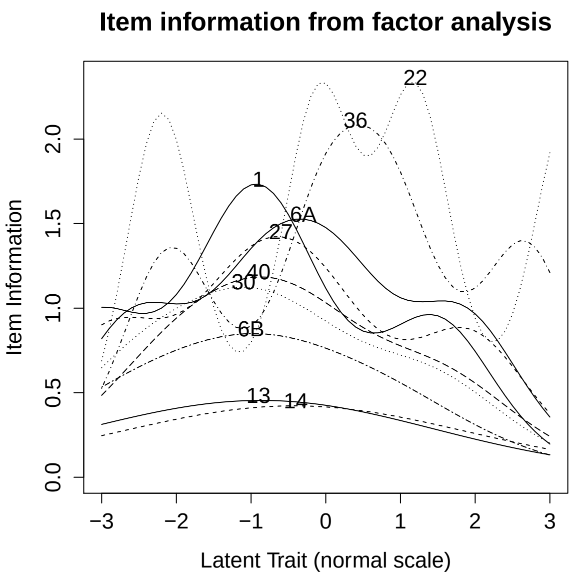
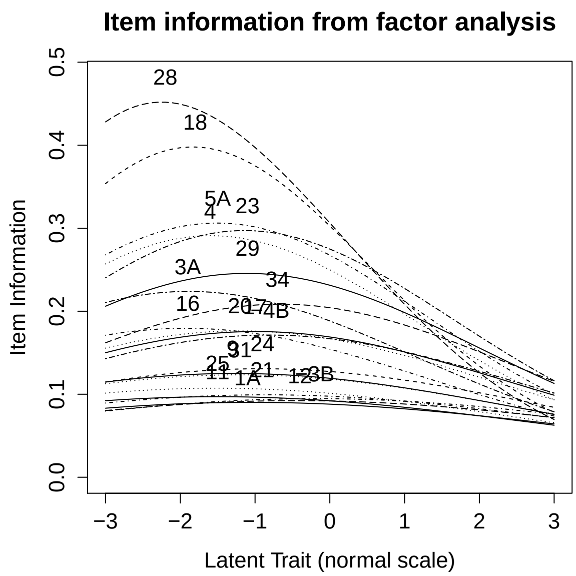


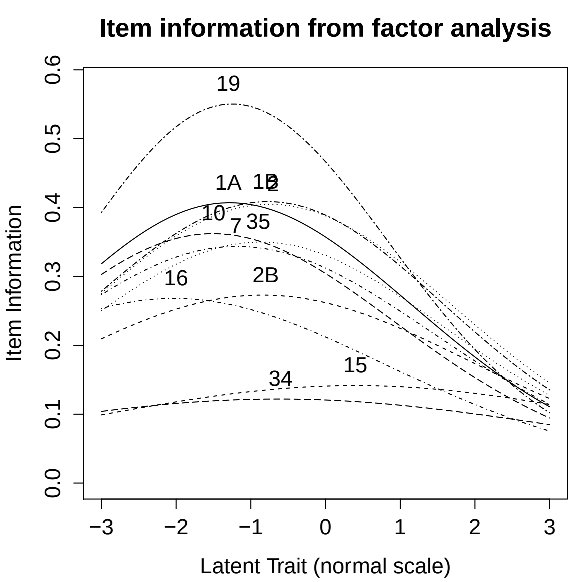
Figure A.5. SAI-II: Item Information Function



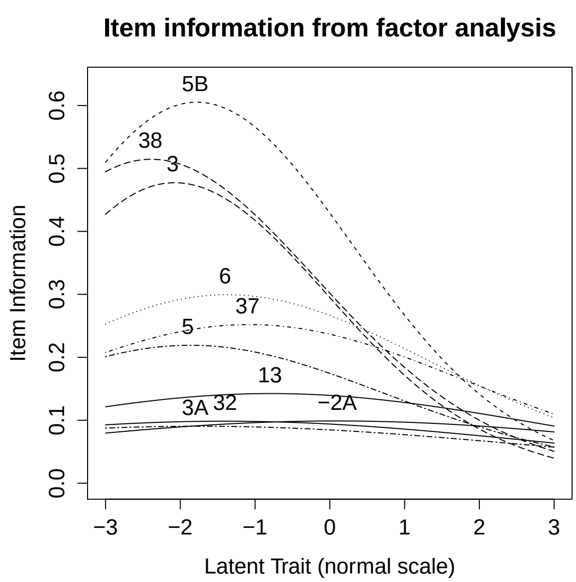
(a) Interest in science



(b) Understanding of science

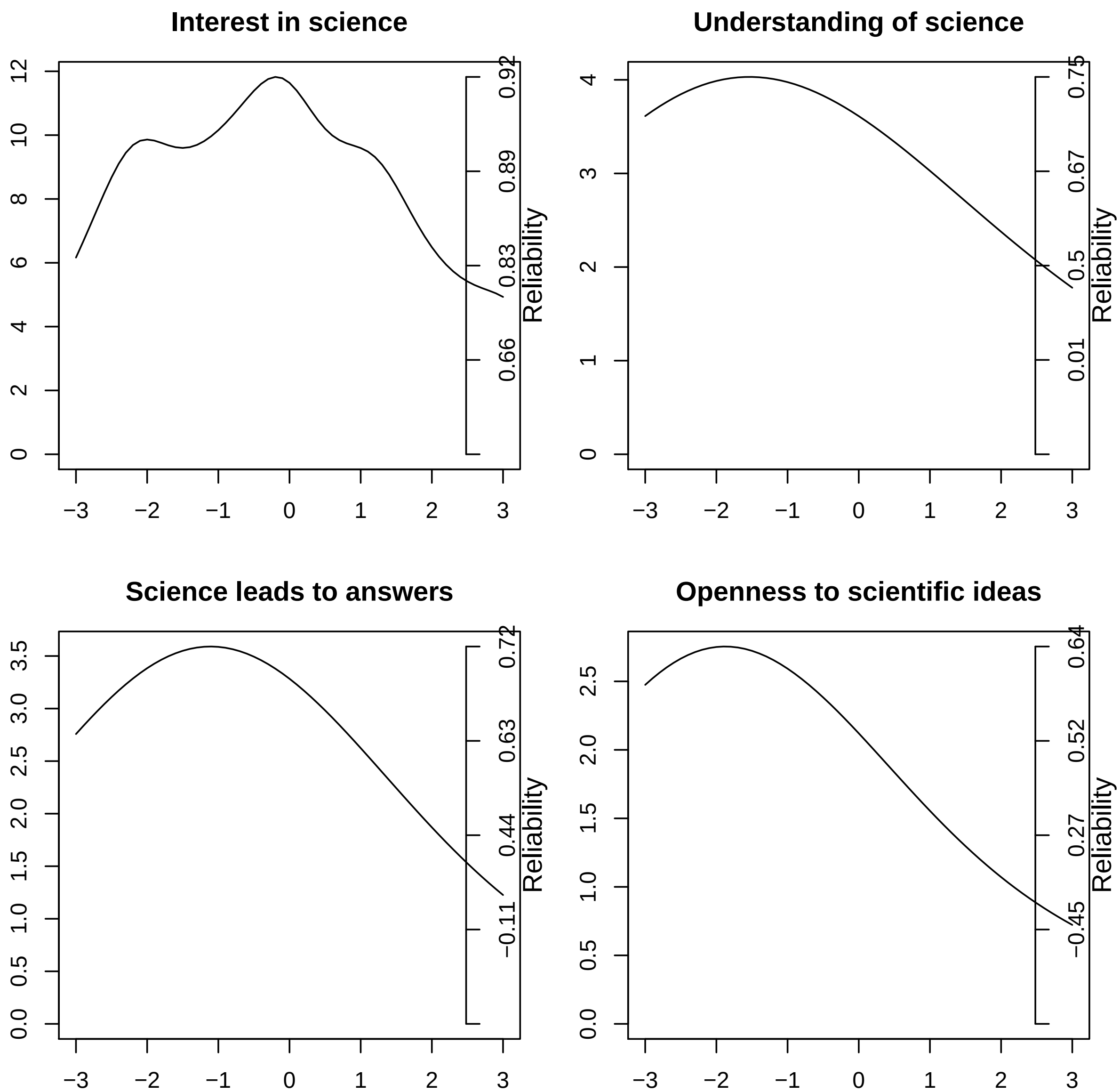


(c) Science leads to answers



(d) Openness to scientific ideas

Figure A.6. SAI-II: Test Information Function



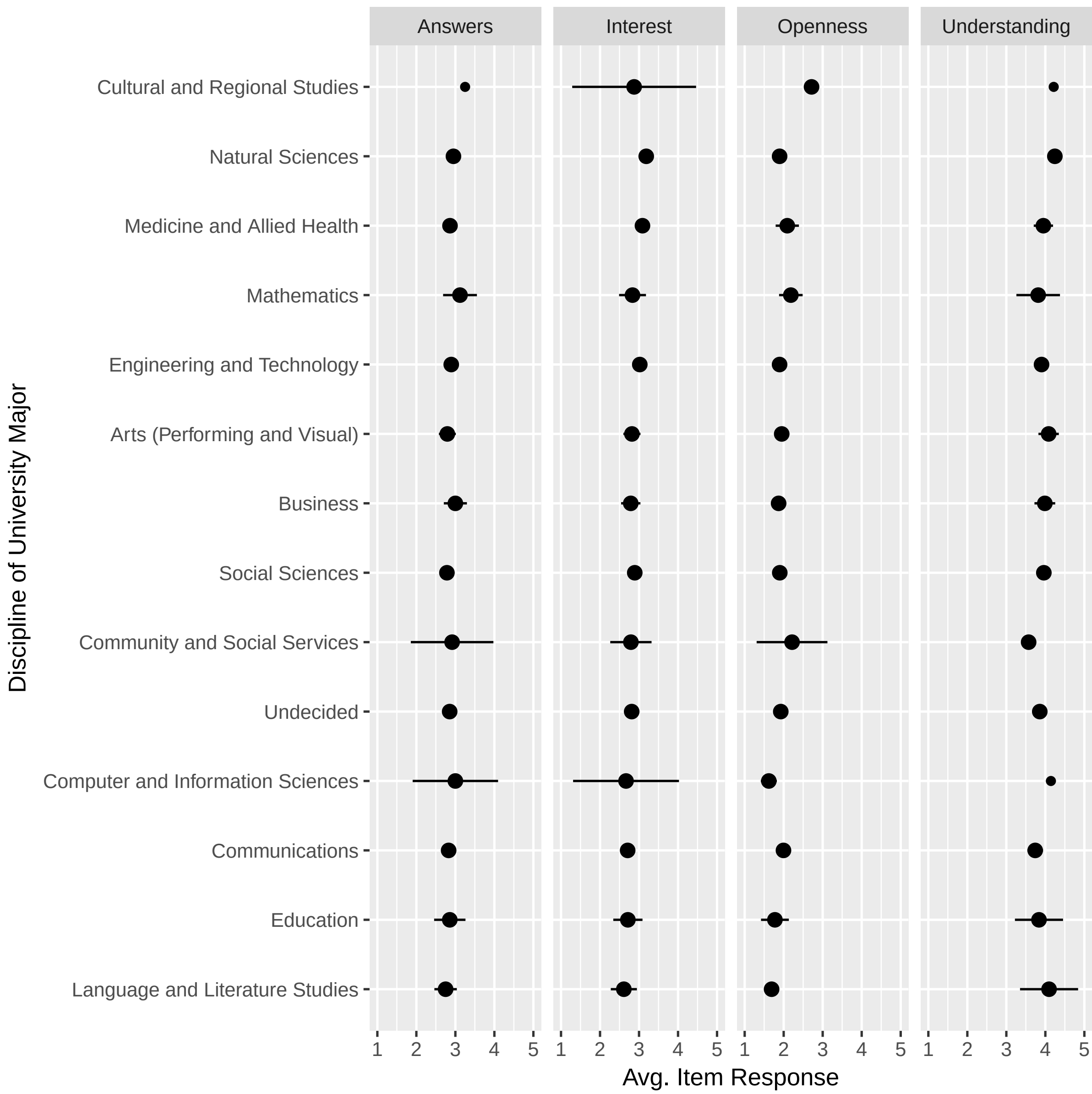


Figure A.7. SAI scores by university discipline.

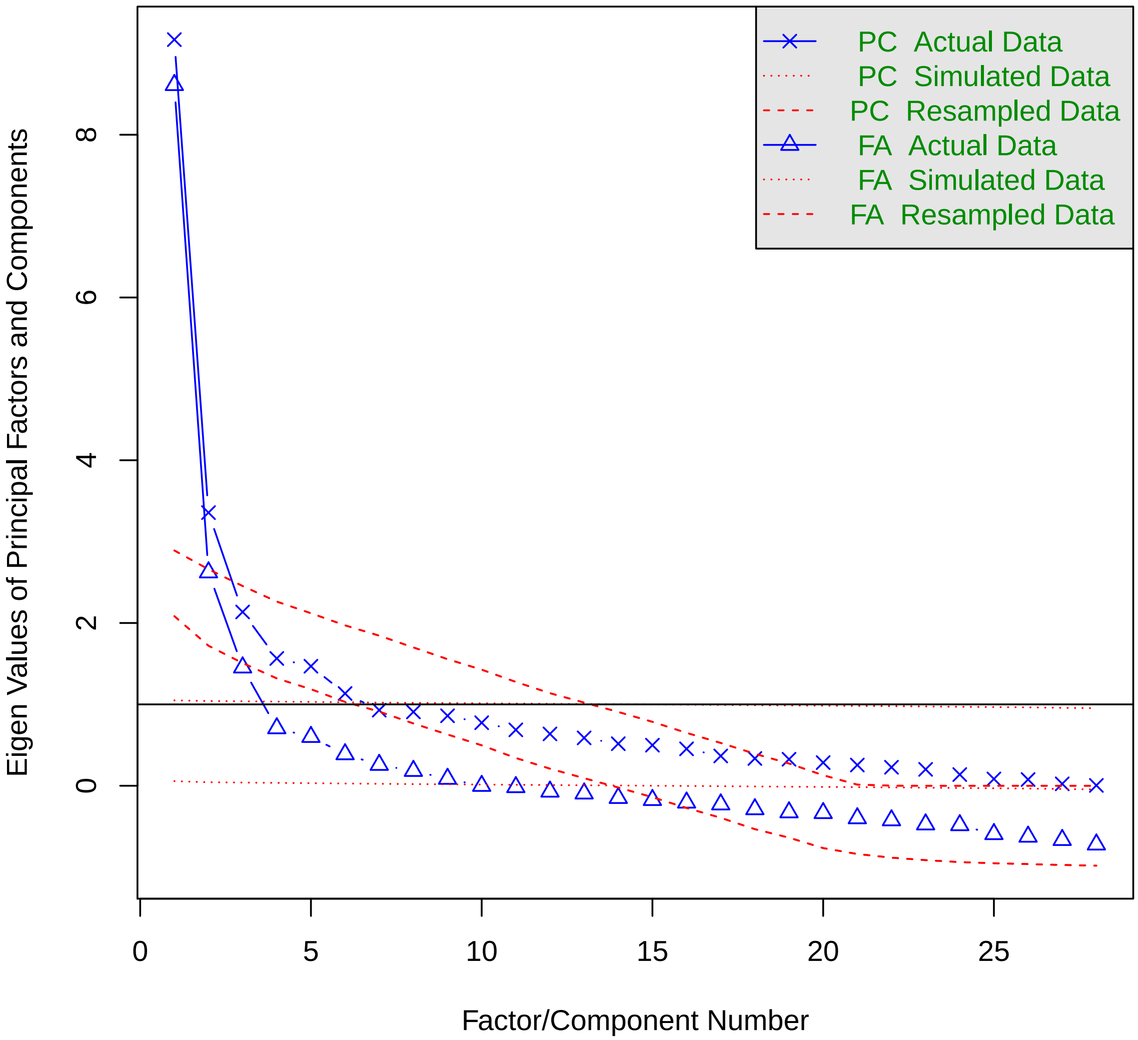


Figure A.8. SAI-III Parallel Analysis and Scree plot.

Figure A.9. SAI-III: Item Information Function

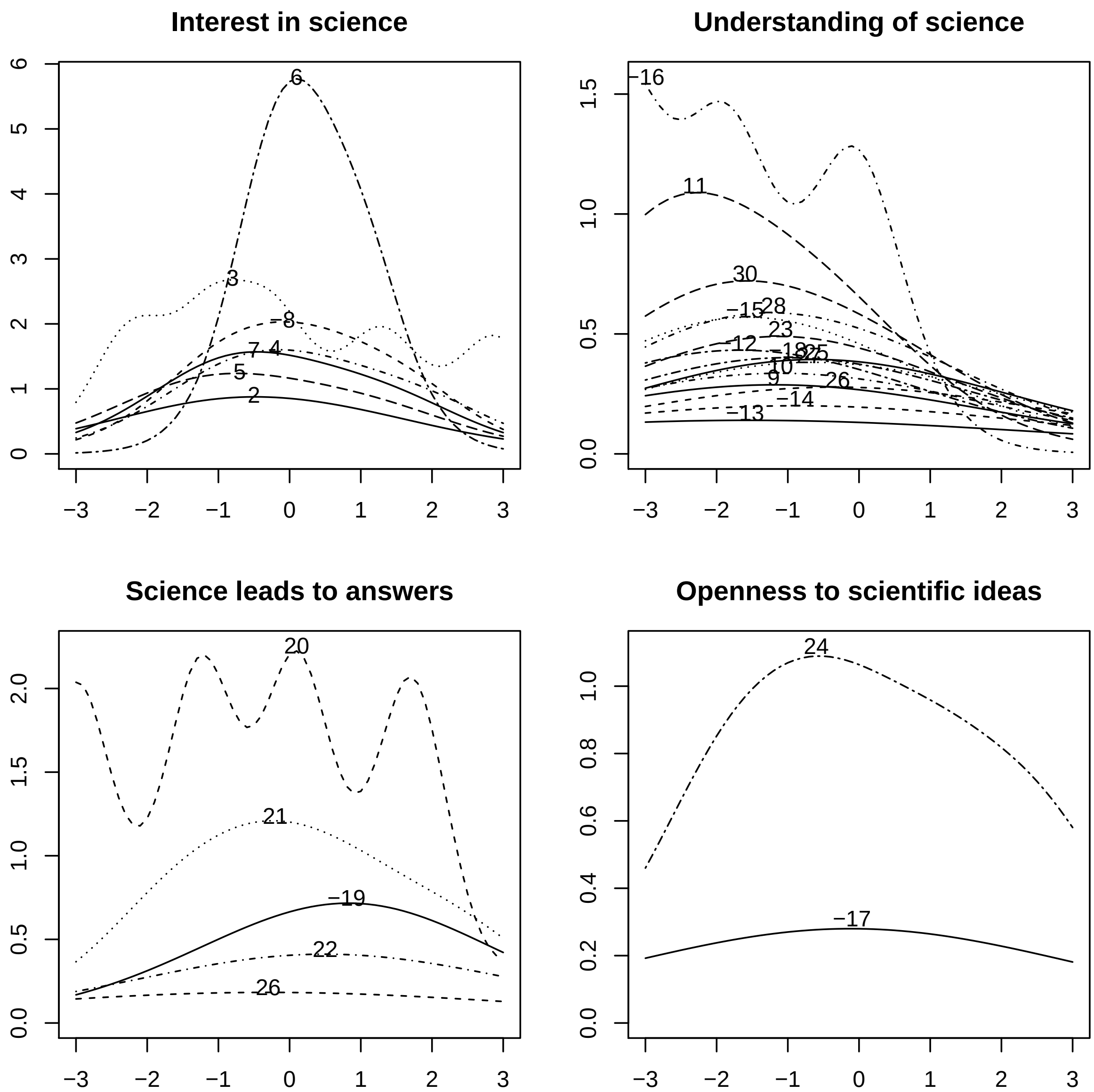
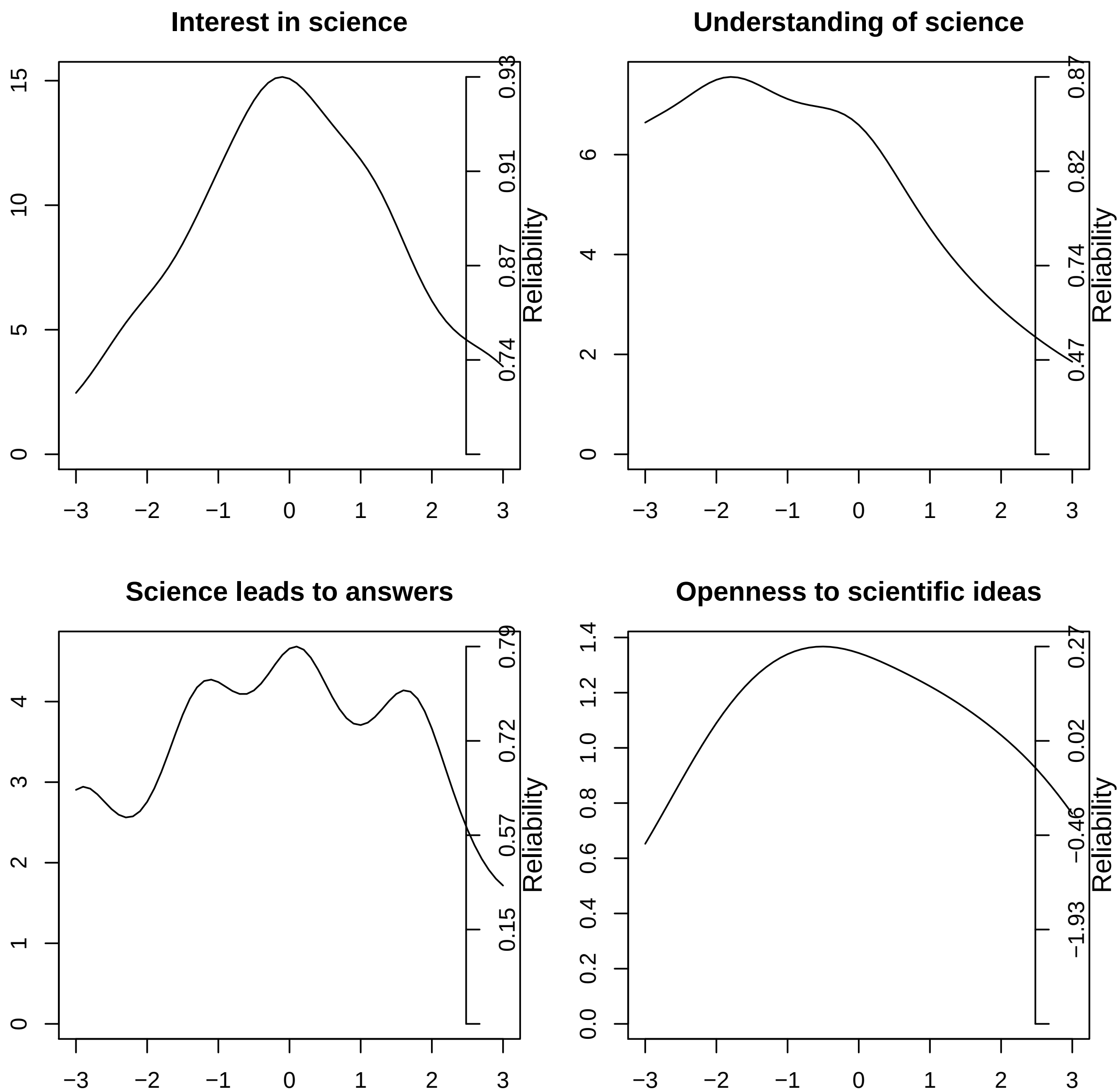


Figure A.10. SAI-III: Test Information Function



List of Tables

Table A.1. Distribution of males and females completing the SAI-II

	Year						
Sex	Freshman	Sophomore	Junior	Senior	Senior +	NA	Sum
Male	73	31	15	13	1	1	134
Female	99	38	10	12	1	1	161
NA	0	0	0	0	0	6	6
Sum	172	69	25	25	2	8	301

Table A.2. SAI-II: Attitude statements.

Item	Attitude Statement
1	I would enjoy studying science.
2	Anything we need to know can be found out through science.
3	It is useless to listen to a new idea unless everybody agrees with it.
4	Scientists are always interested in better explanations of things.
5	If one scientist says an idea is true, all other scientists will believe it.
6	Only highly trained scientists can understand science.
7	We can always get answers to our questions by asking a scientist.
8	Most people are not able to understand science.
9	Electronics are examples of the really valuable products of science.
10	Scientists cannot always find the answers to their questions.
11	When scientists have a good explanation, they do not try to make it better.
12	Most people can understand science.
13	The search for scientific knowledge would be boring.
14	Scientific work would be too hard for me.
15	Scientists discover laws which tell us exactly what is going on in nature.
16	Scientific ideas can be changed.
17	Scientific questions are answered by observing things.
18	Good scientists are willing to change their ideas.
19	Some questions cannot be answered by science.
20	A scientist must have a good imagination to create new ideas.
21	Ideas are the important result of science.
22	I do not want to be a scientist.
23	People must understand science because it affects their lives.
24	A major purpose of science is to produce new drugs and save lives.
25	Scientists must report exactly what they observe.
26	If a scientist cannot answer a question, another scientist can.
27	I would like to work with other scientists to solve scientific problems.
28	Science tries to explain how things happen.
29	Every citizen should understand science.
30	I may not make great discoveries, but working in science would be fun.
31	A major purpose of science is to help people live better.
32	Scientists should not criticize each other's work.
33	The senses are one of the most important tools a scientist has.
34	Scientists believe that nothing is known to be true for sure.
35	Scientific laws have been proven beyond all possible doubt.
36	I would like to be a scientist.
37	Scientists do not have enough time for their families or for fun.
38	Scientific work is useful only to scientists.
39	Scientists have to study too much.
40	Working in a science laboratory would be fun.

Table A.3. SAI-II: Position statements.

Item	Statement
1A	The laws and/or theories of science are approximations of truth and are subject to change.
1B	The laws and/or theories of science represent unchangeable truths discovered through science.
2A	Observation of natural phenomena and experimentation is the basis of scientific explanation. Science is limited in that it can only answer questions about natural phenomena and sometimes it is not able to do that.
2B	The basis of scientific explanation is in authority. Science deals with all problems and it can provide correct answers to all questions.
3A	To operate in a scientific manner, one must display such traits as intellectual honesty, dependence upon objective observation of natural events, and willingness to alter one's position on the basis of sufficient evidence.
3B	To operate in a scientific manner one needs to know what other scientists think; one needs to know all the scientific truths and to be able to take the side of other scientists.
4A	Science is an idea-generating activity. It is devoted to providing explanations of natural phenomena. Its value lies in its theoretical aspects.
4B	Science is a technology-developing activity. It is devoted to serving mankind. Its value lies in its practical uses.
5A	Progress in science requires public support in this age of science; therefore, the public should be made aware of the nature of science and what it attempts to do. The public can understand science and it ultimately benefits from scientific work.
5B	Public understanding of science would contribute nothing to the advancement of science or to human welfare; therefore, the public has no need to understand the nature of science. They cannot understand it and it does not affect them.
6A	Being a scientist or working in a job requiring scientific knowledge and thinking would be a very interesting and rewarding life's work. I would like to do scientific work.
6B	Being a scientist or working in a job requiring scientific knowledge and thinking would be dull and uninteresting; it is only for highly intelligent people who are willing to spend most of their time at work. I would not like to do scientific work.

Item	Mean	SD	Short Description
1	3.50	1.26	Enjoy science
2	2.34	1.09	Know science
3	1.33	0.60	New idea useless
4	4.33	0.81	Better explanations
5	1.26	0.56	Ones scientist true
6	1.83	0.87	Only highly trained
7	1.97	0.97	Always get answers
8	2.55	1.07	Most not able
9	4.21	0.87	Electronics
10	4.34	0.89	Cannot always find
11	1.67	0.77	Good explanation
12	3.42	1.08	Most can understand
13	2.20	1.12	Search for knowledge
14	2.58	1.24	Too hard
15	3.44	1.09	Laws of nature
16	4.60	0.65	Can be changed
17	3.90	0.90	Observing things
18	4.52	0.77	Change ideas
19	4.11	1.07	Some cannot be answered
20	4.04	0.87	Good imagination
21	3.81	0.90	Ideas are important
22	3.23	1.39	Do not want
23	3.97	0.92	People must understand
24	3.91	0.95	New drugs
25	4.49	0.81	Report exactly
26	2.90	1.02	If one cannot answer
27	3.33	1.21	Would like to work
28	4.51	0.65	How things happen
29	3.88	0.87	Every citizen
30	3.51	1.17	Great discoveries
31	4.17	0.86	Help people live better
32	1.55	0.86	Should not criticize
33	3.82	1.00	Senses tool
34	3.68	1.14	Nothing is known
35	2.14	1.15	Proven beyond doubt
36	2.81	1.36	Would like to be
37	2.02	1.00	Not enough time
38	1.31	0.61	Only useful to scientists
39	2.90	1.17	Study too much
40	3.35	1.25	Would be fun

Table A.4. Descriptive statistics for SAI-II attitude items administered in Study 1.

Item	Mean	SD	Short Description
1A	4.09	0.96	Laws are approximations
1B	2.24	1.18	Laws are unchangeable
2A	3.08	1.13	Experimentation is basis
2B	2.20	1.08	Authority is basis
3A	4.54	0.69	Intellectual honesty
3B	3.19	1.14	Need to know all
4A	3.51	1.01	Idea generation
4B	3.79	0.99	Technology developing
5A	4.20	0.84	Public can understand
5B	1.59	0.88	Publc understanding contributes nothing
6A	3.21	1.29	Being a scientist is interesting
6B	2.29	1.13	Being a scientist is dull

Table A.5. Descriptive statistics for SAI-II position items administered in Study 1.

Factors	Eigenvalues of Real Data	Eigenvalues of Random Data
1	6.20	0.81
2	3.62	0.67
3	2.13	0.62
4	1.17	0.57
5	0.91	0.52
6	0.67	0.47
7	0.50	0.43
8	0.46	0.38
9	0.37	0.34
10	0.30	0.30

Table A.6. Comparison of Eigenvalues for the 40 SAI-II Attitudinal Items.

# of Factors	χ^2	df	TLI	RMSEA	VSS	MAP	BIC
1	4049.76	740	0.31	0.13	0.45	0.03	-173.50
2	2902.57	701	0.51	0.11	0.55	0.02	-1098.11
3	2405.53	663	0.59	0.10	0.59	0.01	-1378.29
4	2117.87	626	0.63	0.09	0.54	0.01	-1454.78
5	1895.37	590	0.65	0.09	0.55	0.01	-1471.82
6	1705.18	555	0.67	0.09	0.54	0.01	-1462.27
7	1569.23	521	0.68	0.09	0.53	0.02	-1404.17
8	1456.20	488	0.69	0.09	0.53	0.02	-1328.87
9	1317.14	456	0.70	0.08	0.52	0.02	-1285.30

Table A.7. Exploratory factor solutions 40 attitude items. TLI = Tucker-Lewis Index. RMSEA = Root Mean Sqaure Error of Approximation. VSS = Very Simple Structure. MAP = Velicer's MAP test. BIC = Bayesian Information Criterion.

Table A.8. Three-factor EFA on SAI-II Attitudinal Items

Variable	Interest	Understanding	Answers	h2	u2	com
Do not want	**-0.93**	0.02	-0.03	0.86	0.14	1.0
Would like to be	**0.88**	-0.01	0.12	0.81	0.19	1.0
Enjoy science	**0.87**	0.04	-0.03	0.77	0.23	1.0
Would like to work	**0.86**	-0.06	0.02	0.73	0.27	1.0
Would be fun	**0.82**	-0.07	-0.02	0.65	0.35	1.0
Great discoveries	**0.81**	0.00	-0.01	0.65	0.35	1.0
Search for knowledge	**-0.62**	-0.24	0.10	0.51	0.49	1.4
Too hard	**-0.57**	-0.11	0.07	0.37	0.63	1.1
Not enough time	-0.11	-0.11	0.08	0.04	0.96	2.8
How things happen	-0.18	**0.61**	0.23	0.37	0.63	1.5
Change ideas	0.04	**0.58**	-0.02	0.35	0.65	1.0
Every citizen	0.15	**0.53**	0.27	0.39	0.61	1.7
People must understand	0.17	**0.52**	0.17	0.35	0.65	1.4
New idea useless	0.03	**-0.51**	**0.35**	0.42	0.58	1.8
Can be changed	0.13	**0.51**	**-0.31**	0.43	0.57	1.8
Only useful to scientists	-0.14	**-0.51**	0.18	0.36	0.64	1.4
Ones scientist true	-0.06	**-0.50**	**0.40**	0.46	0.54	1.9
Better explanations	-0.09	**0.49**	0.23	0.25	0.75	1.5
Good explanation	0.00	**-0.47**	0.15	0.26	0.74	1.2
Help people live better	-0.07	**0.42**	0.05	0.17	0.83	1.1
Good imagination	-0.12	**0.38**	0.09	0.14	0.86	1.3
Should not criticize	-0.07	**-0.36**	0.10	0.16	0.84	1.2
New drugs	-0.17	**0.36**	0.06	0.13	0.87	1.5
Report exactly	0.02	**0.31**	-0.12	0.12	0.88	1.3
Electronics	-0.06	**0.31**	0.09	0.10	0.90	1.3
Most can understand	0.01	0.30	0.19	0.11	0.89	1.7
Nothing is known	0.11	0.29	-0.04	0.11	0.89	1.3
Ideas are important	0.09	0.28	0.12	0.11	0.89	1.6
Observing things	-0.02	0.27	0.23	0.11	0.89	1.9
Only highly trained	-0.06	-0.26	0.18	0.12	0.88	1.9
Senses tool	-0.11	0.25	-0.07	0.08	0.92	1.6
Study too much	-0.14	-0.19	-0.04	0.07	0.93	1.9
Most not able	-0.08	-0.19	0.03	0.05	0.95	1.4
Always get answers	0.05	-0.01	**0.70**	0.50	0.50	1.0
Know science	0.18	0.08	**0.61**	0.43	0.57	1.2
Some cannot be answered	-0.11	-0.09	**-0.59**	0.37	0.63	1.1
Cannot always find	0.01	0.15	**-0.49**	0.28	0.72	1.2
Laws of nature	-0.11	0.15	**0.42**	0.18	0.82	1.4
Proven beyond doubt	-0.11	-0.13	**0.38**	0.18	0.82	1.4
If one cannot answer	-0.04	0.04	0.24	0.06	0.94	1.1
SS loadings	5.58	4.31	2.7			
Interest	1.00	0.20	0.11			
Understanding	0.20	1.00	-0.11			
Answers	0.11	-0.11	1.00			

Table A.9. Four-factor EFA on SAI-II Attitudinal Items

Variable	Interest	Understanding	Openness	Answers	h2	u2	com
Do not want	**-0.90**	0.06	0.06	-0.07	0.85	0.15	1.0
Would like to work	**0.90**	0.02	0.11	-0.04	0.77	0.23	1.0
Enjoy science	**0.89**	0.05	0.00	-0.06	0.80	0.20	1.0
Would like to be	**0.88**	0.01	0.03	0.10	0.81	0.19	1.0
Would be fun	**0.83**	-0.03	0.05	-0.05	0.66	0.34	1.0
Great discoveries	**0.83**	0.02	0.02	-0.04	0.67	0.33	1.0
Search for knowledge	**-0.58**	-0.05	**0.31**	-0.01	0.52	0.48	1.6
Too hard	**-0.50**	0.10	**0.34**	-0.11	0.42	0.58	2.0
How things happen	-0.12	**0.64**	-0.02	0.07	0.41	0.59	1.1
People must understand	0.22	**0.52**	-0.06	0.06	0.38	0.62	1.4
Help people live better	0.00	**0.47**	0.02	-0.10	0.23	0.77	1.1
Every citizen	0.16	**0.47**	-0.14	0.22	0.38	0.62	1.9
Change ideas	0.06	**0.46**	-0.25	-0.05	0.36	0.64	1.6
Better explanations	-0.07	**0.43**	-0.12	0.18	0.25	0.75	1.6
New drugs	-0.11	**0.39**	0.01	-0.05	0.16	0.84	1.2
Good imagination	-0.07	**0.38**	-0.03	0.00	0.15	0.85	1.1
Senses tool	-0.03	**0.35**	0.10	-0.24	0.16	0.84	2.0
Observing things	0.02	**0.34**	0.08	0.11	0.13	0.87	1.3
Most can understand	0.05	**0.34**	0.03	0.09	0.13	0.87	1.2
Laws of nature	-0.06	**0.32**	0.26	0.26	0.20	0.80	3.0
Electronics	-0.04	0.29	-0.07	0.05	0.10	0.90	1.2
Nothing is known	0.15	0.28	-0.05	-0.11	0.13	0.87	2.0
Report exactly	0.06	0.27	-0.11	-0.17	0.14	0.86	2.1
Ideas are important	0.08	0.22	-0.11	0.11	0.10	0.90	2.4
Only useful to scientists	-0.03	-0.12	**0.66**	-0.07	0.50	0.50	1.1
New idea useless	0.10	-0.14	**0.62**	0.15	0.49	0.51	1.3
Ones scientist true	-0.04	-0.22	**0.48**	0.29	0.46	0.54	2.1
Not enough time	0.01	0.21	**0.48**	-0.19	0.23	0.77	1.7
Study too much	-0.01	0.10	**0.46**	-0.30	0.25	0.75	1.8
Should not criticize	-0.01	-0.12	**0.41**	-0.04	0.21	0.79	1.2
Can be changed	0.13	0.30	**-0.38**	-0.26	0.42	0.58	3.0
Good explanation	0.02	-0.26	**0.36**	0.08	0.26	0.74	1.9
Only highly trained	-0.01	-0.04	**0.36**	0.04	0.15	0.85	1.1
If one cannot answer	0.01	0.19	0.23	0.11	0.08	0.92	2.4
Most not able	-0.07	-0.10	0.15	0.00	0.05	0.95	2.3
Some cannot be answered	0.00	0.00	0.12	**-0.77**	0.59	0.41	1.1
Know science	0.10	0.07	-0.01	**0.70**	0.53	0.47	1.1
Always get answers	0.06	0.17	0.30	**0.58**	0.48	0.52	1.7
Cannot always find	0.07	0.09	-0.12	**-0.52**	0.32	0.68	1.2
Proven beyond doubt	-0.09	0.04	0.28	0.28	0.18	0.82	2.2
SS loadings	5.46	3.13	3.02	2.5			
Interest	1.00	0.13	-0.18	0.18			
Understanding	0.13	1.00	-0.29	0.01			
Openness	-0.18	-0.29	1.00	0.12			
Answers	0.18	0.01	0.12	1.00			

Factors	Eigenvalues of Real Data	Eigenvalues of Random Data
1	1.85	0.48
2	0.75	0.27
3	0.59	0.20
4	0.21	0.15
5	0.08	0.08
6	-0.01	0.04
7	-0.04	-0.01
8	-0.10	-0.05

Table A.10. Comparison of Eigenvalues for the 12 SAI-II Position Statements

# of Factors	χ^2	df	TLI	RMSEA	VSS	MAP	BIC
1	352.26	54	0.35	0.14	0.36	0.03	44.07
2	237.37	43	0.46	0.12	0.47	0.04	-8.03
3	94.21	33	0.78	0.08	0.50	0.04	-94.12
4	55.09	24	0.85	0.07	0.49	0.06	-81.88
5	26.91	16	0.92	0.05	0.48	0.08	-64.40
6	8.49	9	1.01	0.00	0.50	0.12	-42.88

Table A.11. Exploratory factor solutions for 12 position statements. TLI = Tucker-Lewis Index. RMSEA = Root Mean Sqaure Error of Approximation. VSS = Very Simple Structure. MAP = Velicer's MAP test. BIC = Bayesian Information Criterion.

Table A.12. Three-factor EFA on SAI-II Position Statements

Variable	Interest	Understanding	Authority	h2	u2	com
Being a scientist is dull	**1.00**	0.02	0.02	1.00	0.00	1.0
Being a scientist is interesting	**-0.65**	0.10	0.08	0.47	0.53	1.1
Public can understand	-0.03	**0.80**	0.06	0.66	0.34	1.0
Intellectual honesty	0.02	**0.48**	-0.10	0.24	0.76	1.1
Publc understanding contributes nothing	0.09	**-0.48**	0.29	0.39	0.61	1.8
Technology developing	0.10	**0.39**	0.08	0.14	0.86	1.2
Idea generation	0.13	0.24	0.03	0.05	0.95	1.6
Need to know all	0.12	0.19	0.13	0.05	0.95	2.5
Experimentation is basis	0.01	-0.03	-0.01	0.00	1.00	1.3
Laws are unchangeable	0.02	0.03	**0.81**	0.66	0.34	1.0
Authority is basis	-0.14	-0.06	**0.49**	0.23	0.77	1.2
Laws are approximations	-0.03	0.05	**-0.43**	0.20	0.80	1.0
SS loadings	1.5	1.37	1.22			
Interest	1.00	-0.40	0.20			
Understanding	-0.40	1.00	-0.09			
Authority	0.20	-0.09	1.00			

Table A.13. Four-factor EFA on SAI-II Position Statements

Variable	Interest	Understanding	Distrust	Authority	h2	u2	com
Being a scientist is dull	**1.01**	0.02	0.00	0.01	1.00	0.00	1.0
Being a scientist is interesting	**-0.64**	0.11	0.03	0.10	0.46	0.54	1.1
Public can understand	-0.05	**0.78**	0.01	0.04	0.63	0.37	1.0
Publc understanding contributes nothing	0.12	**-0.45**	0.07	**0.43**	0.50	0.50	2.2
Intellectual honesty	0.00	**0.44**	0.00	-0.17	0.24	0.76	1.3
Technology developing	0.12	**0.44**	0.14	0.21	0.20	0.80	1.8
Idea generation	0.13	0.24	0.05	0.06	0.05	0.95	1.8
Need to know all	0.13	0.21	0.04	0.18	0.07	0.93	2.7
Laws are approximations	-0.01	0.01	**1.00**	-0.01	1.00	0.00	1.0
Experimentation is basis	0.02	-0.02	0.09	0.06	0.01	0.99	1.9
Authority is basis	-0.12	0.02	-0.05	**0.60**	0.37	0.63	1.1
Laws are unchangeable	0.08	0.08	-0.30	**0.49**	0.41	0.59	1.8
SS loadings	1.52	1.34	1.15	0.94			
Interest	1.00	-0.37	-0.13	0.16			
Understanding	-0.37	1.00	0.05	-0.12			
Distrust	-0.13	0.05	1.00	-0.25			
Authority	0.16	-0.12	-0.25	1.00			

Factors	Eigenvalues of Real Data	Eigenvalues of Random Data
1	8.14	0.97
2	4.60	0.83
3	2.97	0.76
4	1.58	0.70
5	1.20	0.66
6	0.99	0.62
7	0.86	0.58
8	0.59	0.53
9	0.46	0.49
10	0.41	0.45

Table A.14. Comparison of Eigenvalues for the 52 SAI-II Items.

# of Factors	χ^2	df	TLI	RMSEA	VSS	MAP	BIC
1	6794.88	1274	0.26	0.13	0.48	0.03	-475.98
2	5188.27	1223	0.45	0.11	0.56	0.02	-1791.53
3	4466.53	1173	0.52	0.10	0.56	0.01	-2227.91
4	4090.22	1124	0.55	0.10	0.55	0.01	-2324.57
5	3767.04	1076	0.57	0.10	0.52	0.01	-2373.81
6	3513.33	1029	0.58	0.09	0.55	0.01	-2359.29
7	3251.66	983	0.60	0.09	0.53	0.01	-2358.43
8	3107.18	938	0.60	0.09	0.53	0.01	-2246.09

Table A.15. Exploratory factor solutions for 52-items. TLI = Tucker-Lewis Index. RMSEA = Root Mean Sqaure Error of Approximation. VSS = Very Simple Structure. MAP = Velicer's MAP test. BIC = Bayesian Information Criterion.

Table A.16. Three-factor EFA on SAI-II Items

Variable	Interest	Openness	Understanding	h2	u2	com
Do not want	**-0.94**	0.05	-0.03	0.87	0.13	1.0
Would like to be	**0.90**	-0.02	0.12	0.82	0.18	1.0
Being a scientist is interesting	**0.87**	0.03	0.03	0.78	0.22	1.0
Enjoy science	**0.87**	0.01	-0.02	0.76	0.24	1.0
Would like to work	**0.86**	-0.04	0.05	0.73	0.27	1.0
Great discoveries	**0.82**	-0.02	0.00	0.66	0.34	1.0
Would be fun	**0.82**	-0.07	-0.02	0.64	0.36	1.0
Being a scientist is dull	**-0.76**	-0.08	0.16	0.64	0.36	1.1
Search for knowledge	**-0.61**	-0.25	0.12	0.53	0.47	1.4
Too hard	**-0.57**	-0.05	0.08	0.35	0.65	1.1
Not enough time	-0.11	-0.10	0.08	0.04	0.96	2.7
Experimentation is basis	0.01	0.00	-0.01	0.00	1.00	2.2
How things happen	-0.19	**0.63**	0.12	0.37	0.63	1.2
Public can understand	0.18	**0.61**	0.14	0.45	0.55	1.3
Intellectual honesty	-0.02	**0.56**	-0.08	0.33	0.67	1.1
Change ideas	0.03	**0.56**	-0.11	0.35	0.65	1.1
People must understand	0.16	**0.55**	0.10	0.36	0.64	1.2
Every citizen	0.16	**0.53**	0.18	0.35	0.65	1.4
Better explanations	-0.09	**0.50**	0.15	0.24	0.76	1.3
Publc understanding contributes nothing	-0.13	**-0.46**	0.28	0.38	0.62	1.8
Help people live better	-0.08	**0.45**	0.00	0.19	0.81	1.1
Only useful to scientists	-0.13	**-0.45**	0.25	0.35	0.65	1.8
Good imagination	-0.12	**0.41**	0.03	0.16	0.84	1.2
Good explanation	0.01	**-0.41**	0.22	0.24	0.76	1.5
Technology developing	-0.07	**0.40**	0.21	0.17	0.83	1.6
New drugs	-0.17	**0.38**	-0.02	0.15	0.85	1.4
Electronics	-0.07	**0.34**	0.06	0.11	0.89	1.1
Report exactly	-0.01	**0.33**	-0.12	0.13	0.87	1.3
Should not criticize	-0.07	**-0.32**	0.21	0.18	0.82	1.9
Observing things	-0.02	0.30	0.18	0.10	0.90	1.7
Most can understand	0.04	0.29	0.14	0.10	0.90	1.5
Ideas are important	0.08	0.29	0.06	0.10	0.90	1.2
Nothing is known	0.10	0.27	-0.15	0.13	0.87	1.9
Senses tool	-0.12	0.26	-0.09	0.08	0.92	1.7
Idea generation	-0.10	0.24	0.08	0.06	0.94	1.6
Only highly trained	-0.05	-0.24	0.23	0.14	0.86	2.1
Study too much	-0.13	-0.18	-0.02	0.06	0.94	1.9
Most not able	-0.10	-0.15	0.06	0.05	0.95	2.1
Always get answers	0.09	0.09	**0.65**	0.42	0.58	1.1
Laws are unchangeable	-0.12	-0.03	**0.61**	0.40	0.60	1.1
Know science	0.19	0.17	**0.59**	0.40	0.60	1.4
Authority is basis	0.08	-0.11	**0.53**	0.32	0.68	1.1
Cannot always find	-0.01	0.03	**-0.53**	0.29	0.71	1.0
Some cannot be answered	-0.15	-0.17	**-0.53**	0.32	0.68	1.4
Proven beyond doubt	-0.09	0.00	**0.50**	0.26	0.74	1.1
Laws of nature	-0.11	0.25	**0.44**	0.22	0.78	1.7
Can be changed	0.11	**0.41**	**-0.43**	0.44	0.56	2.1
New idea useless	0.03	**-0.41**	**0.43**	0.40	0.60	2.0
Ones scientist true	-0.04	**-0.40**	**0.42**	0.40	0.60	2.0
Laws are approximations	0.11	0.12	**-0.35**	0.17	0.83	1.4
Need to know all	-0.11	0.24	0.27	0.11	0.89	2.3
If one cannot answer	-0.02	0.11	0.24	0.06	0.94	1.4
SS loadings	7.1	5.3	3.92			
Interest	1.00	0.25	0.01			
Openness	0.25	1.00	-0.16			
Understanding	0.01	-0.16	1.00			

Table A.17. Four-factor EFA on SAI-II Items

Variable	Interest	Openness	Answers	Understanding	h2	u2	com
Do not want	**-0.94**	0.05	-0.03	0.00	0.87	0.13	1.0
Would like to be	**0.91**	0.02	0.08	0.07	0.82	0.18	1.0
Enjoy science	**0.89**	0.06	-0.09	0.10	0.80	0.20	1.1
Being a scientist is interesting	**0.87**	0.01	0.04	-0.04	0.78	0.22	1.0
Would like to work	**0.87**	0.00	0.01	0.08	0.74	0.26	1.0
Would be fun	**0.82**	-0.04	-0.05	0.05	0.65	0.35	1.0
Great discoveries	**0.82**	-0.02	0.00	-0.02	0.66	0.34	1.0
Being a scientist is dull	**-0.74**	0.04	0.06	0.25	0.66	0.34	1.2
Search for knowledge	**-0.58**	-0.09	-0.01	**0.34**	0.57	0.43	1.7
Too hard	**-0.55**	0.03	0.00	0.17	0.36	0.64	1.2
How things happen	-0.17	**0.62**	0.05	-0.06	0.38	0.62	1.2
Public can understand	0.18	**0.54**	0.13	-0.17	0.45	0.55	1.6
Change ideas	0.05	**0.53**	-0.17	-0.09	0.38	0.62	1.3
People must understand	0.17	**0.51**	0.06	-0.10	0.36	0.64	1.3
Better explanations	-0.08	**0.48**	0.11	-0.06	0.24	0.76	1.2
Every citizen	0.15	**0.46**	0.18	-0.16	0.35	0.65	1.8
Technology developing	-0.05	**0.44**	0.12	0.07	0.19	0.81	1.2
Intellectual honesty	-0.03	**0.44**	-0.03	-0.28	0.33	0.67	1.7
Good imagination	-0.10	**0.41**	-0.02	-0.03	0.17	0.83	1.1
Help people live better	-0.08	**0.40**	-0.01	-0.11	0.19	0.81	1.2
New drugs	-0.16	**0.39**	-0.08	-0.02	0.16	0.84	1.4
Observing things	0.01	**0.38**	0.05	0.16	0.14	0.86	1.4
Nothing is known	0.15	**0.37**	**-0.32**	0.18	0.27	0.73	2.8
Electronics	-0.06	**0.35**	0.00	-0.01	0.12	0.88	1.1
Report exactly	0.01	**0.32**	-0.17	-0.04	0.15	0.85	1.6
Senses tool	-0.10	0.30	-0.18	0.06	0.12	0.88	2.0
Need to know all	-0.10	0.29	0.19	0.10	0.12	0.88	2.2
Most can understand	0.05	0.29	0.09	0.00	0.10	0.90	1.3
Good explanation	0.02	-0.29	0.16	0.25	0.24	0.76	2.6
Ideas are important	0.09	0.28	0.02	-0.02	0.10	0.90	1.2
Idea generation	-0.09	0.26	0.02	0.04	0.06	0.94	1.3
Some cannot be answered	-0.13	-0.10	**-0.62**	0.13	0.41	0.59	1.2
Know science	0.19	0.19	**0.57**	0.05	0.41	0.59	1.5
Laws are unchangeable	-0.11	0.04	**0.57**	0.18	0.40	0.60	1.3
Laws are approximations	0.16	0.25	**-0.56**	0.24	0.39	0.61	2.0
Cannot always find	0.00	0.01	**-0.55**	-0.05	0.32	0.68	1.0
Always get answers	0.11	0.22	**0.52**	0.28	0.42	0.58	2.0
Proven beyond doubt	-0.10	0.01	**0.51**	0.05	0.28	0.72	1.1
Authority is basis	0.08	-0.03	**0.49**	0.17	0.32	0.68	1.3
Can be changed	0.12	**0.35**	**-0.46**	-0.16	0.47	0.53	2.3
Laws of nature	-0.09	**0.31**	**0.35**	0.13	0.22	0.78	2.4
New idea useless	0.09	-0.13	0.20	**0.62**	0.52	0.48	1.3
Only useful to scientists	-0.08	-0.17	0.01	**0.62**	0.49	0.51	1.2
Publc understanding contributes nothing	-0.08	-0.20	0.08	**0.56**	0.47	0.53	1.4
Not enough time	-0.05	0.15	-0.18	**0.50**	0.24	0.76	1.5
Only highly trained	0.00	-0.01	0.03	**0.48**	0.24	0.76	1.0
Ones scientist true	0.00	-0.19	0.26	**0.46**	0.42	0.58	2.0
Study too much	-0.09	-0.01	-0.19	**0.35**	0.15	0.85	1.7
Experimentation is basis	0.06	0.17	-0.20	**0.33**	0.13	0.87	2.3
Should not criticize	-0.05	-0.17	0.11	**0.32**	0.20	0.80	1.9
If one cannot answer	0.01	0.22	0.11	0.23	0.09	0.91	2.5
Most not able	-0.08	-0.04	-0.04	0.22	0.07	0.93	1.4
SS loadings	7.05	4.35	3.49	3.31			
Interest	1.00	0.22	0.03	-0.16			
Openness	0.22	1.00	-0.07	-0.26			
Answers	0.03	-0.07	1.00	0.21			
Understanding	-0.16	-0.26	0.21	1.00			

	χ^2	df	TLI	RMSEA	SRMR	BIC
CFA models						
Three-factor	2510.60	1224	0.68	0.06	0.09	38894.56
Four-factor	2544.92	1274	0.69	0.06	0.09	39769.00

Table A.18. CFA fit statistics for SAI-II models.

	Latent	Observed Item	Estimate	S.E.	Z	P Value
1	Interest	22	-1.24	0.06	-19.48	0.00
2	Interest	36	1.17	0.06	18.46	0.00
3	Interest	6A	1.11	0.06	18.35	0.00
4	Interest	1	1.05	0.06	17.42	0.00
5	Interest	27	0.98	0.06	16.85	0.00
6	Interest	30	0.90	0.06	15.56	0.00
7	Interest	40	0.94	0.06	14.82	0.00
8	Interest	6B	-0.81	0.06	-13.90	0.00
9	Interest	13	-0.67	0.06	-11.03	0.00
10	Interest	14	-0.65	0.07	-9.58	0.00
11	Understanding	5A	0.48	0.05	9.18	0.00
12	Understanding	23	0.50	0.06	8.79	0.00
13	Understanding	29	0.48	0.05	8.85	0.00
14	Understanding	28	0.26	0.04	6.06	0.00
15	Understanding	18	0.32	0.05	6.41	0.00
16	Understanding	4B	0.36	0.06	5.55	0.00
17	Understanding	20	0.28	0.06	4.86	0.00
18	Understanding	34	0.29	0.08	3.87	0.00
19	Understanding	12	0.36	0.07	5.15	0.00
20	Understanding	4	0.24	0.05	4.57	0.00
21	Understanding	31	0.31	0.06	5.59	0.00
22	Understanding	24	0.30	0.06	4.80	0.00
23	Understanding	9	0.24	0.06	4.16	0.00
24	Understanding	21	0.25	0.06	4.22	0.00
25	Understanding	3B	0.22	0.08	2.89	0.00
26	Understanding	17	0.22	0.06	3.66	0.00
27	Understanding	26	0.15	0.07	2.24	0.03
28	Understanding	33	0.26	0.07	4.00	0.00
29	Understanding	4A	0.19	0.07	2.77	0.01
30	Understanding	25	0.15	0.05	2.79	0.01
31	Openness	1B	0.65	0.07	8.83	0.00
32	Openness	1A	-0.38	0.06	-6.14	0.00
33	Openness	19	-0.56	0.07	-8.28	0.00
34	Openness	35	0.54	0.07	7.41	0.00
35	Openness	2	0.60	0.07	8.82	0.00
36	Openness	7	0.52	0.06	8.57	0.00
37	Openness	2B	0.53	0.07	7.63	0.00
38	Openness	10	-0.36	0.06	-6.31	0.00
39	Openness	16	-0.20	0.04	-4.70	0.00
40	Openness	15	0.38	0.07	5.34	0.00
41	Answers	3	0.39	0.04	10.33	0.00
42	Answers	5B	0.50	0.06	9.05	0.00
43	Answers	37	0.29	0.07	4.38	0.00
44	Answers	38	0.32	0.04	8.22	0.00
45	Answers	5	0.28	0.04	7.69	0.00
46	Answers	6	0.36	0.06	6.25	0.00
47	Answers	3A	-0.25	0.05	-5.40	0.00
48	Answers	39	0.26	0.08	3.37	0.00
49	Answers	11	0.29	0.05	5.80	0.00
50	Answers	32	0.26	0.06	4.51	0.00
51	Answers	2A	0.15	0.08	1.96	0.05
52	Answers	8	0.24	0.07	3.27	0.00

Table A.19. Parameter estimates for 4-factor CFA.

Table A.20. IRT Analysis: Interest in Science

Interest in Science

	Item information at θ						
Item	-3	-2	-1	0	1	2	3
6A	0.84	1.02	1.36	1.49	1.06	0.98	0.36
1	0.99	1.08	1.69	1.12	0.90	0.72	0.19
27	0.89	0.96	1.36	1.23	0.82	0.86	0.37
30	0.65	1.00	1.12	0.92	0.72	0.50	0.20
36	0.53	1.36	0.89	1.92	1.81	1.12	1.22
40	0.48	0.93	1.17	1.03	0.77	0.55	0.24
6B	0.54	0.76	0.85	0.77	0.56	0.31	0.13
13	0.32	0.41	0.46	0.43	0.34	0.23	0.13
14	0.25	0.35	0.41	0.42	0.36	0.26	0.17
22	0.79	1.98	0.75	2.41	2.28	0.94	1.82
	Summary statistics at θ						
Test.info	6.26	9.86	10.07	11.74	9.63	6.47	4.84
SEM	0.40	0.32	0.32	0.29	0.32	0.39	0.45
Reliability	0.84	0.90	0.90	0.91	0.90	0.85	0.79

Table A.21. IRT Analysis: Understanding of Science

Understanding of Science

Item	Item information at θ -3	-2	-1	0	1	2	3
4	0.27	0.30	0.30	0.26	0.20	0.14	0.09
16	0.16	0.16	0.16	0.14	0.12	0.09	0.07
34	0.16	0.19	0.20	0.20	0.18	0.15	0.11
11	0.09	0.09	0.09	0.09	0.08	0.07	0.06
15	0.08	0.09	0.09	0.09	0.09	0.08	0.07
3A	0.21	0.23	0.22	0.19	0.15	0.11	0.08
17	0.15	0.17	0.18	0.17	0.15	0.13	0.10
18	0.34	0.39	0.37	0.30	0.21	0.13	0.08
25	0.09	0.09	0.09	0.09	0.08	0.07	0.06
3B	0.08	0.09	0.10	0.10	0.10	0.09	0.08
20	0.15	0.16	0.16	0.16	0.14	0.11	0.09
21	0.09	0.10	0.10	0.10	0.09	0.08	0.07
28	0.41	0.43	0.39	0.30	0.21	0.13	0.07
4B	0.14	0.15	0.16	0.16	0.14	0.12	0.10
9	0.11	0.12	0.12	0.11	0.10	0.09	0.07
24	0.10	0.11	0.11	0.11	0.10	0.09	0.08
31	0.10	0.10	0.11	0.10	0.09	0.08	0.07
5A	0.26	0.30	0.30	0.26	0.21	0.15	0.10
12	0.08	0.09	0.09	0.09	0.09	0.08	0.07
23	0.24	0.28	0.29	0.27	0.22	0.17	0.12
29	0.21	0.25	0.26	0.24	0.21	0.16	0.11
	Summary statistics at θ						
Test.info	3.51	3.88	3.87	3.53	2.97	2.34	1.76
SEM	0.53	0.51	0.51	0.53	0.58	0.65	0.75
Reliability	0.72	0.74	0.74	0.72	0.66	0.57	0.43

Table A.22. IRT Analysis: Openness in Science

Openness in Science

Item	Item information at θ						
	-3	-2	-1	0	1	2	3
1A	0.11	0.19	0.31	0.42	0.49	0.47	0.38
16	0.07	0.12	0.18	0.24	0.30	0.33	0.31
34	0.11	0.13	0.16	0.17	0.17	0.16	0.14
1B	0.14	0.23	0.33	0.41	0.43	0.38	0.29
15	0.11	0.13	0.13	0.14	0.13	0.11	0.10
35	0.13	0.20	0.29	0.36	0.39	0.35	0.27
10	0.10	0.15	0.22	0.28	0.33	0.33	0.28
19	0.11	0.19	0.30	0.40	0.46	0.43	0.34
2B	0.12	0.16	0.21	0.24	0.25	0.23	0.19
2	0.14	0.20	0.27	0.32	0.32	0.29	0.23
7	0.11	0.16	0.22	0.26	0.28	0.27	0.23
	Summary statistics at θ						
Test.info	1.23	1.87	2.61	3.25	3.55	3.36	2.76
SEM	0.90	0.73	0.62	0.55	0.53	0.55	0.60
Reliability	0.19	0.46	0.62	0.69	0.72	0.70	0.64

Table A.23. IRT Analysis: Science Leads to Answers

Science Leads to Answers

Item	Item information at θ						
	-3	-2	-1	0	1	2	3
7	0.07	0.08	0.09	0.10	0.10	0.10	0.09
3A	0.06	0.07	0.08	0.09	0.09	0.09	0.09
3	0.04	0.08	0.17	0.30	0.42	0.49	0.44
5	0.06	0.09	0.14	0.19	0.23	0.24	0.22
32	0.06	0.07	0.08	0.09	0.09	0.09	0.09
5B	0.06	0.13	0.27	0.46	0.63	0.69	0.58
6	0.10	0.16	0.22	0.28	0.31	0.31	0.26
38	0.05	0.10	0.18	0.29	0.41	0.48	0.47
13	0.09	0.11	0.13	0.14	0.14	0.14	0.12
37	0.10	0.14	0.17	0.20	0.21	0.20	0.18
	Summary statistics at θ						
Test.info	0.70	1.04	1.54	2.13	2.64	2.82	2.54
SEM	1.20	0.98	0.81	0.68	0.62	0.60	0.63
Reliability	-0.44	0.04	0.35	0.53	0.62	0.65	0.61

Item	N	Mean	SD	Domain
3802	921	3.97	1.58	Interest
3803	909	3.44	1.74	Interest
3804	930	3.31	1.72	Interest
3805	920	3.88	1.57	Interest
3806	930	3.05	1.80	Interest
3807	930	3.59	1.73	Interest
3808	930	3.63	1.84	Interest
3809	894	5.00	1.24	Openness
3810	894	4.77	1.18	Openness
3811	966	5.20	1.05	Openness
3812	917	1.67	1.02	Openness
3813	923	1.69	0.96	Openness
3814	908	2.36	1.32	Openness
3815	925	1.86	1.11	Openness
3816	890	1.83	1.06	Openness
3817	913	3.37	1.25	Openness
3818	948	2.31	1.29	Openness
3819	898	4.45	1.51	Answers
3820	933	3.35	1.55	Answers
3821	932	3.41	1.49	Answers
3822	884	2.92	1.39	Answers
3823	905	4.82	1.31	Understanding
3824	922	3.43	1.35	Understanding
3825	907	4.21	1.34	Understanding
3826	931	3.92	1.39	Understanding
3827	908	4.28	1.35	Understanding
3828	895	4.64	1.17	Understanding
3830	901	4.87	1.13	Understanding

Table A.24. Descriptive statistics for SAI-III items administered in Study 2.

Factors	Eigenvalues of Real Data	Eigenvalues of Random Data
1	8.35	0.63
2	2.86	0.50
3	1.37	0.43
4	0.63	0.38
5	0.55	0.33
6	0.33	0.29
7	0.24	0.25
8	0.14	0.22
9	0.05	0.18
10	-0.02	0.15

Table A.25. Comparison of Eigenvalues for the 27 SAI-III Items.

# of Factors	χ^2	df	TLI	RMSEA	VSS	MAP	BIC
1	295077.02	350	0.42	0.15	0.71	0.03	291370.67
2	212580.12	323	0.58	0.13	0.59	0.02	209159.69
3	156548.39	297	0.66	0.12	0.58	0.02	153403.28
4	136238.43	272	0.66	0.11	0.56	0.02	133358.06
5	122242.17	248	0.67	0.11	0.56	0.02	119615.95
6	105350.25	225	0.68	0.11	0.50	0.02	102967.59
1	90636.11	203	0.42	0.11	0.50	0.02	88486.42
2	80664.02	182	0.58	0.11	0.50	0.02	78736.72
3	72571.16	162	0.66	0.11	0.43	0.03	70855.64
4	62841.69	143	0.66	0.11	0.44	0.03	61327.38
5	55061.74	125	0.67	0.11	0.43	0.04	53738.04
6	51677.33	108	0.68	0.11	0.44	0.04	50533.66

Table A.26. Exploratory factor solutions. TLI = Tucker-Lewis Index. RMSEA = Root Mean Sqaure Error of Approximation. VSS = Very Simple Structure. MAP = Velicer's MAP test. BIC = Bayesian Information Criterion.

Table A.27. Three-factor EFA on SAI-III

Variable	Interest	Understanding	Answers	h2	u2	com
Like to do science	**0.95**	0.01	0.00	0.91	0.09	1.0
Like to be a scientist	**0.94**	-0.07	0.02	0.85	0.15	1.0
Science lab would be fun	**0.87**	-0.07	-0.08	0.66	0.34	1.0
Like to work at science	**0.83**	0.06	0.03	0.76	0.24	1.0
Do not want to be scientist	**-0.80**	0.06	0.01	0.61	0.39	1.0
Science would be fun	**0.80**	0.07	0.01	0.70	0.30	1.0
Science would be interesting	**0.71**	0.20	0.08	0.73	0.27	1.2
People can understand	0.20	0.11	0.07	0.09	0.91	1.9
Public no need to understand	0.09	**-0.75**	-0.02	0.51	0.49	1.0
Alter ideas based on evidence	-0.01	**0.74**	-0.07	0.52	0.48	1.0
Only useful to scientists	-0.02	**-0.68**	0.11	0.45	0.55	1.1
Useless unless everybody agrees	-0.01	**-0.63**	0.24	0.40	0.60	1.3
Public ultimately benefits	0.10	**0.61**	0.19	0.52	0.48	1.2
Goals of science	0.06	**0.59**	0.18	0.47	0.53	1.2
Willing to change ideas	0.21	**0.57**	-0.06	0.44	0.56	1.3
Objective observation	0.09	**0.54**	0.04	0.35	0.65	1.1
Intellectually honest	0.13	**0.51**	0.07	0.35	0.65	1.2
Does not contribute progress	0.08	**-0.50**	-0.05	0.24	0.76	1.1
People must understand	0.12	**0.47**	**0.31**	0.47	0.53	1.9
Public support	0.03	**0.43**	0.27	0.32	0.68	1.7
Other scientists will believe	0.01	**-0.42**	0.30	0.22	0.78	1.8
High trained scientists	0.11	**-0.41**	0.23	0.18	0.82	1.8
Anything can be found	0.08	0.02	**0.77**	0.67	0.33	1.0
Eventually find answers	-0.02	0.02	**0.75**	0.56	0.44	1.0
Answers by asking scientist	0.09	-0.07	**0.60**	0.41	0.59	1.1
Cannot be answered	0.05	0.12	**-0.60**	0.33	0.67	1.1
Every citizen should	0.10	**0.42**	**0.43**	0.50	0.50	2.1
Public generally unable	-0.01	0.03	0.13	0.02	0.98	1.1
SS loadings	5.48	5.02	2.73			
Interest	1.00	0.40	0.45			
Understanding	0.40	1.00	0.18			
Answers	0.45	0.18	1.00			

Table A.28. Four-factor EFA on SAI-III

Variable	Interest	Understanding	Answers	Openness	h2	u2	com
Like to do science	**0.96**	-0.04	0.03	-0.06	0.92	0.08	1.0
Like to be a scientist	**0.93**	-0.02	0.01	0.06	0.85	0.15	1.0
Science lab would be fun	**0.88**	-0.12	-0.04	-0.03	0.67	0.33	1.0
Like to work at science	**0.82**	0.10	0.00	0.03	0.76	0.24	1.0
Do not want to be scientist	**-0.80**	0.06	-0.01	-0.01	0.61	0.39	1.0
Science would be fun	**0.80**	0.06	0.01	-0.03	0.70	0.30	1.0
Science would be interesting	**0.70**	0.27	0.02	0.03	0.73	0.27	1.3
People can understand	0.21	0.06	0.08	-0.08	0.09	0.91	1.8
Alter ideas based on evidence	-0.03	**0.70**	-0.16	-0.16	0.58	0.42	1.2
Objective observation	0.06	**0.59**	-0.06	-0.05	0.40	0.60	1.1
People must understand	0.10	**0.58**	0.20	0.01	0.50	0.50	1.3
Every citizen should	0.07	**0.58**	0.30	0.06	0.53	0.47	1.6
Intellectually honest	0.11	**0.56**	-0.03	-0.04	0.39	0.61	1.1
Public ultimately benefits	0.11	**0.54**	0.13	-0.19	0.52	0.48	1.5
Willing to change ideas	0.19	**0.53**	-0.12	-0.13	0.46	0.54	1.5
Public support	0.01	**0.53**	0.17	0.01	0.35	0.65	1.2
Goals of science	0.07	**0.51**	0.13	-0.19	0.47	0.53	1.5
Public generally unable	-0.06	0.28	0.01	0.24	0.07	0.93	2.1
Anything can be found	0.10	0.11	**0.75**	0.04	0.68	0.32	1.1
Cannot be answered	0.01	0.23	**-0.73**	0.13	0.48	0.52	1.3
Eventually find answers	0.00	0.10	**0.72**	0.04	0.57	0.43	1.1
Answers by asking scientist	0.10	0.08	**0.55**	0.13	0.40	0.60	1.2
High trained scientists	0.02	0.18	0.04	**0.67**	0.40	0.60	1.1
Only useful to scientists	-0.08	-0.19	-0.01	**0.62**	0.55	0.45	1.2
Does not contribute progress	0.02	-0.09	-0.18	**0.52**	0.33	0.67	1.3
Public no need to understand	0.04	**-0.37**	-0.08	**0.51**	0.54	0.46	1.9
Useless unless everybody agrees	-0.05	-0.23	0.15	**0.49**	0.42	0.58	1.7
Other scientists will believe	-0.03	-0.09	0.22	**0.39**	0.24	0.76	1.7
SS loadings	5.48	4.05	2.42	2.27			
Interest	1.00	0.45	0.39	-0.12			
Understanding	0.45	1.00	0.21	-0.41			
Answers	0.39	0.21	1.00	0.07			
Openness	-0.12	-0.41	0.07	1.00			

Table A.29. SAI-III IRT Analysis: Interest in Science

Interest in Science

Item	Item information at θ						
	-3	-2	-1	0	1	2	3
3802	0.66	1.28	1.55	1.38	1.10	0.68	0.26
3803	2.22	1.79	2.90	2.43	1.43	1.75	1.52
3804	0.25	0.95	1.78	1.90	1.55	1.23	0.68
3805	0.65	1.34	1.59	1.35	1.13	0.80	0.33
3806	0.10	0.78	2.18	2.75	2.03	1.68	1.56
3807	0.33	0.91	1.51	1.54	1.25	0.80	0.33
3808	0.24	0.63	1.18	1.47	1.26	0.75	0.32
	Summary statistics at θ						
Test.info	4.45	7.68	12.71	12.82	9.74	7.70	4.99
SEM	0.47	0.36	0.28	0.28	0.32	0.36	0.45
Reliability	0.78	0.87	0.92	0.92	0.90	0.87	0.80

Table A.30. SAI-III IRT Analysis: Openness to Sciencee

Openness to Sciencee

Item	Item information at θ						
	-3	-2	-1	0	1	2	3
3809	0.13	0.19	0.26	0.32	0.34	0.33	0.28
3810	0.14	0.22	0.31	0.38	0.42	0.40	0.33
3811	0.08	0.18	0.36	0.60	0.81	0.91	0.80
3812	0.07	0.16	0.32	0.54	0.75	0.84	0.74
3813	0.11	0.15	0.21	0.26	0.29	0.29	0.27
3814	0.13	0.18	0.22	0.25	0.26	0.25	0.21
3815	0.07	0.18	0.39	0.67	0.91	1.00	0.86
3816	0.08	0.18	0.36	0.59	0.78	0.84	0.74
3818	0.15	0.21	0.29	0.34	0.37	0.34	0.29
	Summary statistics at θ						
Test.info	0.96	1.66	2.71	3.95	4.93	5.21	4.52
SEM	1.02	0.78	0.61	0.50	0.45	0.44	0.47
Reliability	-0.04	0.40	0.63	0.75	0.80	0.81	0.78

Table A.31. SAI-III IRT Analysis: Science Leads to Answers

Science Leads to Answers

Item	Item information at θ -3	-2	-1	0	1	2	3
3819	0.16	0.32	0.54	0.73	0.79	0.68	0.45
3820	0.33	0.75	1.15	1.28	1.12	0.84	0.51
3821	0.46	1.01	1.36	1.41	1.18	0.89	0.70
3822	0.21	0.35	0.50	0.60	0.60	0.51	0.37
	Summary statistics at θ						
Test.info	1.16	2.44	3.55	4.01	3.68	2.92	2.03
SEM	0.93	0.64	0.53	0.50	0.52	0.59	0.70
Reliability	0.14	0.59	0.72	0.75	0.73	0.66	0.51

Table A.32. SAI-III IRT Analysis: Understanding of Science

Understanding of Science

Item	Item information at θ						
	-3	-2	-1	0	1	2	3
3823	0.35	0.44	0.46	0.42	0.33	0.23	0.14
3824	0.12	0.14	0.16	0.16	0.16	0.15	0.13
3825	0.74	1.05	1.11	0.99	0.80	0.52	0.23
3826	0.53	0.87	1.02	0.96	0.82	0.58	0.30
3827	0.34	0.46	0.52	0.50	0.42	0.30	0.19
3828	0.62	0.78	0.78	0.67	0.50	0.31	0.15
3830	0.56	0.69	0.69	0.57	0.41	0.25	0.13
	Summary statistics at θ						
Test.info	3.26	4.43	4.75	4.29	3.43	2.32	1.27
SEM	0.55	0.47	0.46	0.48	0.54	0.66	0.89
Reliability	0.69	0.77	0.79	0.77	0.71	0.57	0.22

Table A.33. Descriptive statistics for administered scales. All scales have a range of 1 through 6, except for the ICAR, which are based on the average of dichotomous items.

Scale	Items	N	Mean	SD
SAI-III	Interest In Science	2324	3.74	0.54
SAI-III	Openness to Science	2324	2.85	0.28
SAI-III	Science Leads to Answers	2324	3.66	0.48
SAI-III	Understanding Science	2324	4.38	0.41
IPIP-100	Agreeableness	2324	4.85	0.21
IPIP-100	Conscientiousness	2324	4.30	0.22
IPIP-100	Extraversion	2324	3.63	0.24
IPIP-100	Intellect	2324	4.93	0.20
IPIP-100	Emotional Stability	2324	3.67	0.22
Big Five Aspects Scales	Assertiveness	2324	4.34	0.30
Big Five Aspects Scales	Compassion	2324	4.95	0.24
Big Five Aspects Scales	Enthusiasm	2324	4.10	0.23
Big Five Aspects Scales	Industriousness	2324	3.99	0.22
Big Five Aspects Scales	Intellect	2324	4.91	0.25
Big Five Aspects Scales	Openness	2324	5.03	0.21
Big Five Aspects Scales	Orderliness	2324	4.26	0.28
Big Five Aspects Scales	Politeness	2324	2.43	0.23
Big Five Aspects Scales	Volatility	2324	3.48	0.26
Big Five Aspects Scales	Withdrawal	2324	3.59	0.26
ORVIS	Adventure	2324	2.21	0.41
ORVIS	Altruism	2324	3.48	0.30
ORVIS	Analysis	2324	2.46	0.44
ORVIS	Creativity	2324	3.02	0.34
ORVIS	Erudition	2324	2.96	0.39
ORVIS	Leadership	2324	2.79	0.35
ORVIS	Organizational	2324	2.88	0.32
ORVIS	Production	2324	2.61	0.41
ICAR	ICAR	2324	0.38	0.06
ICAR	Letters and Numbers	2324	0.62	0.15
ICAR	Matrix Reasoning	2324	0.53	0.12
ICAR	3D Rotation	2324	0.03	0.05
ICAR	Verbal Reasoning	2324	0.66	0.08

Table A.34. Correlations of IPIP 20-item traits with SAI-III factors.

Variable	IIS	OS	SLA	US	Agr	Cnsc	Ext	Int	Emt
Interest In Science	1.00	0.01	0.19***	0.36***	−0.06**	−0.01	−0.02	0.19***	−0.05*
Openness to Science		1.00	0.08***	0.01	−0.03	0.02	−0.04*	−0.03	0.04*
Science Leads to Answers			1.00	0.19***	0.01	0.07**	−0.02	0.04*	0.00
Understanding Science				1.00	0.00	−0.01	0.01	0.18***	−0.03
Agreeableness					1.00	0.30***	0.37***	0.16***	−0.16***
Conscientiousness						1.00	0.26***	0.11***	−0.19***
Extraversion							1.00	0.28***	−0.19***
Intellect								1.00	−0.11***
Emotional Stability									1.00

Note: $^{***}p < .001$; $^{**}p < .01$; $^{*}p < .05$.

Table A.35. Correlations of 10-item Big Five Aspects Scales with SAI-III factors.

Variable	IIS	OS	SLA	Und	Assr	Cmps	Ent	Inds	Int	Opn	Ord	P	V	W
Interest In Science	1.00	0.01	0.19^{***}	0.36^{***}	0.01	-0.06^{**}	-0.06^{**}	0.02	0.18^{***}	0.07^{**}	-0.01	0.10^{***}	-0.09^{***}	0.00
Openness to Science		1.00	0.08^{***}	0.01	-0.02	-0.08^{***}	-0.01	-0.01	-0.02	-0.03	0.03	0.05^{**}	0.02	0.03
Science Leads to Answers			1.00	0.19^{***}	0.01	-0.01	0.01	0.03	0.06^{**}	0.00	0.06^{**}	0.02	-0.03	0.01
Understanding Science				1.00	0.01	0.01	-0.06^{**}	0.02	0.15^{***}	0.10^{***}	0.01	0.04^{*}	-0.05^{*}	0.00
Assertiveness					1.00	0.19^{***}	0.31^{***}	0.34^{***}	0.35^{***}	0.11^{***}	0.14^{***}	0.10^{***}	-0.08^{***}	-0.32^{***}
Compassion						1.00	0.33^{***}	0.16^{***}	0.11^{***}	0.20^{***}	0.08^{***}	-0.31^{***}	-0.09^{***}	-0.10^{***}
Enthusiasm							1.00	0.18^{***}	0.08^{***}	0.10^{***}	0.14^{***}	-0.11^{***}	-0.04	-0.18^{***}
Industriousness								1.00	0.26^{***}	-0.03	0.28^{***}	-0.11^{***}	-0.29^{***}	-0.37^{***}
Intellect									1.00	0.21^{***}	0.03	0.05^{*}	-0.16^{***}	-0.25^{***}
Openness										1.00	-0.05^{*}	-0.05^{*}	0.03	0.06^{**}
Orderliness											1.00	-0.10^{***}	0.01	-0.06^{**}
Politeness												1.00	0.15^{***}	0.04
Volatility													1.00	0.45^{***}
Withdrawal														1.00

Note: $^{***}p < .001$; $^{**}p < .01$; $^{*}p < .05$.

Table A.36. Correlations of the Oregon Vocational Interest Scales with SAI-III factors, corrected for attenuation.

Variable	IntIS	OpntS	ScLtA	UndrS	Advnt	Altrs	Anlys	Crtvt	Erdtn	Ldrsh	Orgnz	Prdct
Interest In Science	1.00	0.01	0.19***	0.36***	0.16***	0.08***	0.52***	0.13***	0.20***	0.11***	0.12***	0.22***
Openness to Science		1.00	0.08***	0.01	0.08***	0.04	0.06**	0.02	0.02	0.05*	0.07***	0.04
Science Leads to Answers			1.00	0.19***	0.07***	0.04*	0.17***	0.01	0.06**	0.03	0.09***	0.07***
Understanding Science				1.00	0.05*	0.04	0.29***	0.10***	0.22***	0.14***	0.05*	0.11***
Adventure					1.00	0.13***	0.27***	0.19***	0.16***	0.29***	0.19***	0.40***
Altruism						1.00	0.09***	0.21***	0.22***	0.23***	0.15***	0.17***
Analysis							1.00	0.20***	0.31***	0.27***	0.23***	0.29***
Creativity								1.00	0.43***	0.27***	0.04*	0.30***
Erudition									1.00	0.27***	0.09***	0.25***
Leadership										1.00	0.35***	0.19***
Organizational											1.00	0.18***
Production												1.00

Note: ***$p < .001$; **$p < .01$; *$p < .05$.

Table A.37. Correlations of ICAR Ability Items with SAI-III factors.

A correlation table from the psych package in R. Adjust for multiple tests = holm

Variable	IntIS	OpntS	ScLtA	UndrS	ICAR6	LttaN	MtrxR	3DRtt	Verbl
Interest In Science	1.00	0.01	0.19***	0.36***	0.23***	0.17***	0.14***	0.18***	0.17***
Openness to Science		1.00	0.08***	0.01	−0.02	−0.01	−0.01	0.01	−0.04
Science Leads to Answers			1.00	0.19***	0.01	0.02	−0.01	−0.02	0.03
Understanding Science				1.00	0.22***	0.18***	0.10***	0.14***	0.18***
ICAR 60					1.00	0.75***	0.72***	0.66***	0.67***
Letter and Number						1.00	0.40***	0.34***	0.33***
Matrix Reasoning							1.00	0.30***	0.29***
3D Rotation								1.00	0.31***
Verbal									1.00

Note: $^{***}p < .001$; $^{**}p < .01$; $^{*}p < .05$.

	Estimate	Std. Error	z value	Pr(>|z|)
(Intercept)	-6.1749	1.3248	-4.66	0.0000
ORVIS Analysis	0.6050	0.1231	4.92	0.0000
ICAR Total	3.8277	0.8916	4.29	0.0000
Intellect	0.5289	0.2737	1.93	0.0533

Table A.38. Logistic Regression of STEM Major onto ORVIS Analysis, ICAR Total, and Intellect.

	Estimate	Std. Error	z value	Pr(>|z|)
(Intercept)	-6.9692	1.5030	-4.64	0.0000
Analysis	0.3871	0.1389	2.79	0.0053
ICAR Total	3.4130	0.9039	3.78	0.0002
Intellect	0.4279	0.2735	1.56	0.1177
Interest In Science	0.3186	0.1150	2.77	0.0056
Openness To Science	-0.0260	0.1854	-0.14	0.8886
Science Leads To Answers	-0.0471	0.1077	-0.44	0.6623
Understanding of Science	0.2365	0.1411	1.68	0.0938

Table A.39. Logistic Regression of STEM Major onto ORVIS Analysis, ICAR Total, Intellect, and the SAI-III scales.

Vars	N	Mean	SD	Min	Max	Range	SE
Vocabulary	363058	5.66	2.28	0	9	9	0.00
Memory for Sentences	367746	8.98	3.09	0	16	16	0.01
Memory for Words	367730	11.30	5.41	0	24	24	0.01
Information Total	358050	192.53	59.85	0	376	376	0.10
Disguised Words	367376	14.53	7.04	0	30	30	0.01
English Total	363268	79.80	14.75	0	113	113	0.02
Word Functions in Sentences	367162	9.84	5.44	0	24	24	0.01
Reading Comphrension	367579	28.98	11.08	0	48	48	0.02
Creativity	367088	8.44	4.00	0	20	20	0.01
Mechanical Reasoning	366874	10.21	4.33	0	20	20	0.01
Visualization in 2D	367130	12.45	5.82	0	24	24	0.01
Visualization in 3D	366965	8.34	3.28	0	16	16	0.01
Abstract Reasoning	366825	8.66	3.12	0	15	15	0.01
Arithmetic Reasoning	367184	8.05	3.60	0	16	16	0.01
High School Math	367335	10.15	4.78	0	24	24	0.01
Advanced Math	363219	3.04	2.27	0	14	14	0.00

Table A.40. Descriptive Statistics for Project TALENT Ability Scales.

Table A.41. One-factor EFA on Project TALENT Ability Items

Variable	g	h2	u2	com
Reading Comphrehension	**0.85**	0.73	0.27	1
Arithmetic Reasoning	**0.79**	0.63	0.37	1
High School Math	**0.78**	0.60	0.40	1
Word Functions In Sentences	**0.73**	0.53	0.47	1
Creativity	**0.72**	0.52	0.48	1
Vocabulary	**0.71**	0.51	0.49	1
Abstract Reasoning	**0.71**	0.50	0.50	1
Disguised Words	**0.66**	0.44	0.56	1
Mechanical Reasoning	**0.61**	0.37	0.63	1
Visualization in 3D	**0.60**	0.36	0.64	1
Memory for Words	**0.54**	0.29	0.71	1
English Total	**0.53**	0.28	0.72	1
Advanced Math	**0.52**	0.27	0.73	1
Visualization in 2D	**0.48**	0.23	0.77	1
Memory for Sentences	**0.34**	0.12	0.88	1
Information Total	0.26	0.07	0.93	1
SS loadings	6.46			
Proportion Var	0.4			

Table A.42. Descriptive statistics for Project TALENT Scales.

Variables	Mean	SD	Min	Max	Range	SE
Physical Knowledge	8.03	4.10	0.00	18.00	18.00	0.01
Biological Knowledge	5.73	2.42	0.00	11.00	11.00	0.00
Scientific Attitudes	5.77	2.03	0.00	10.00	10.00	0.00
Number of Science Courses	1.96	1.25	1.00	6.00	5.00	0.00
Socioability	6.55	2.94	0.00	12.00	12.00	0.00
Social Sensitivity	4.55	2.36	0.00	9.00	9.00	0.00
Impulsiveness	1.94	1.63	0.00	9.00	9.00	0.00
Vigor	3.58	2.13	0.00	7.00	7.00	0.00
Calmness	4.15	2.51	0.00	9.00	9.00	0.00
Tidiness	5.55	2.81	0.00	11.00	11.00	0.00
Culture	5.11	2.37	0.00	10.00	10.00	0.00
Leadership	1.28	1.35	0.00	5.00	5.00	0.00
Self-confidence	5.03	2.46	0.00	12.00	12.00	0.00
Mature personality	10.93	5.19	0.00	24.00	24.00	0.01
Cognitive Ability	0.00	0.99	-0.85	6.28	7.13	0.00

Table A.43. Pearson Correlations between Scientific Attitudes and Domains and PTPI Scales.

Variable	PS	BS	SA	SC	Scb	Scl	Impl	Vig	Clm	Tdn	Cul	Ldr	Slf	Mtr
Physical Science	1.00													
Biological Science	0.63	1.00												
Scientific Attitude	0.47	0.47	1.00											
Science Courses	0.22	0.18	0.20	1.00										
Socioability	−0.01	0.01	0.10	0.04	1.00									
Social Sensitivity	0.06	0.10	0.17	0.13	0.52	1.00								
Impulsiveness	0.05	0.06	0.06	0.07	0.24	0.22	1.00							
Vigor	0.13	0.13	0.14	0.07	0.51	0.43	0.25	1.00						
Calmness	0.15	0.16	0.19	0.12	0.44	0.58	0.16	0.43	1.00					
Tidiness	0.03	0.05	0.10	0.09	0.43	0.54	0.12	0.41	0.53	1.00				
Culture	0.05	0.09	0.14	0.14	0.46	0.62	0.20	0.43	0.53	0.60	1.00			
Leadership	0.06	0.05	0.05	0.12	0.35	0.40	0.26	0.40	0.38	0.33	0.41	1.00		
Self-confidence	0.14	0.14	0.15	0.10	0.38	0.30	0.12	0.32	0.44	0.29	0.31	0.30	1.00	
Mature personality	0.17	0.16	0.17	0.15	0.41	0.58	0.20	0.51	0.61	0.62	0.59	0.48	0.41	1.00

Table A.44. Pearson Correlations between Scientific Attitudes and Domain Knowledge and Cognitive Ability.

Variable	PhysS	BlgcS	ScntA	ScncC	CgntA
Physical Science	1.00				
Biological Science	0.63	1.00			
Scientific Attitude	0.47	0.47	1.00		
Science Courses	0.22	0.18	0.20	1.00	
Cognitive Ability	0.09	0.08	0.08	0.06	1.00

Table A.45. Proposed Revision of SAI-II

SAI-III		
Factor	Description	SAPA Item #
Interest in Science	Doing science would be a very interesting and rewarding life's work.	3802
Interest in Science	I would like to do scientific work.	3803
Interest in Science	I would like to work with other scientists to solve scientific problems.	3804
Interest in Science	I may not make great discoveries, but working in science would be fun.	3805
Interest in Science	I would like to be a scientist.	3806
Interest in Science	Working in a science laboratory would be fun.	3807
Interest in Science	I do not want to be a scientist.	3808
Opennness to Science	Scientists must be intellectually honest.	3809
Openness to Science	Science requires objective observation of natural events.	3810
Openness to Science	Scientists must be willing to alter their ideas on the basis of new evidence.	3811
Openness to Science	It is useless to listen to a new idea unless everybody agrees with it.	3812
Openness to Science	If one scientist says an idea is true, all other scientists will believe it.	3813
Openness to Science	Only highly trained scientists can understand science.	3814
Openness to Science	Scientific work is useful only to scientists.	3815
Openness to Science	The public has no need to understand science.	3816
Openness to Science	Public understanding of science does not contribute to progress.	3818
Science Leads to Answers	Some questions cannot be answered by science.	3819
Science Leads to Answers	Science will eventually find answers to all questions.	3820
Science Leads to Answers	Anything we need to know can be found out through science.	3821
Science Leads to Answers	We can always get answers to our questions by asking a scientist.	3822
Understanding of Science	Good scientists are willing to change their ideas.	3823
Understanding of Science	Most people can understand science.	3824
Understanding of Science	People must understand science because it affects their lives.	3825
Understanding of Science	Every citizen should understand science.	3826
Understanding of Science	Progress in science requires public support.	3827
Understanding of Science	The public should be made aware of the nature and goals of science.	3828
Understanding of Science	The public ultimately benefits from scientific work.	3830