WORK SATISFACTION THROUGH PERSON-ENVIRONMENT FIT: INTEGRATING ABILITY, PERSONALITY, AND INTEREST

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ABSTRACT

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Person-environment fit research typically examines one domain at a time (e.g., values) which leaves career choosers and counselors uninformed about how to weigh different types of fit. With a national sample of high school students followed several years after graduation, this study pursues two main goals: (1) map the associations between ability, personality, and interest domains, and (2) assess the relative importance of fit across these domains in the prediction of future work satisfaction. Results echo previous findings on the primacy of the environment in PE fit and the utility of Prediger's (1982) meta-dimensions in an integrative framework for individual differences. While the domains showed differential predictive validity (i.e., abilities > personality > interests), the nature of those fit relationships varied substantially, both within and between domains, with scant evidence of strict congruence effects overall. Implications for theory and practice are discussed with an emphasis on job tasks and complexity.

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INTRODUCTION

Historically, humans had little choice in the kind of work they did. A pre-agricultural child would learn the skills of hunter-gatherers in order to meet basic physiological needs. Even the children of farmers and craftspeople would most likely grow up to do the same work as their parents (Savickas, 2008). Only with industrialization, urbanization, and the rapid increase in the specialization of labor have some humans had the luxury (or burden) of choosing which daily activities will help them to survive biologically and even thrive psychologically. Industrial jobs were more narrowly defined than the loose collection of chores required to maintain a farm. In this sense, modernization allowed more choice and mobility but also entailed more standardized roles with less autonomy in how those roles were implemented. Industrialization not only made career choice more possible, but it also raised the stakes on fitting people to work since a bad match to a narrow job could produce a particularly negative working experience. Additionally, specialization may have strengthened a feedback loop between individual identity and work. A person's identity informs career choice, and as jobs become more unique, work roles have greater potential impact on individual identity.

The proliferation of career options since the Industrial Revolution has created even more interesting challenges for modern humans. While unprecedented freedom in career choice increases our potential for extraordinary achievement and fulfillment in work, it may also create an "overchoice syndrome" (Rysiew et al., 1994). Additionally, as jobs appear, mutate, and disappear at faster rates, the collective challenge of maximizing productivity within those jobs requires more informed decisions. Given that people change jobs more frequently, single career choices early in life may be less restrictive than they once were. However, there are still substantial switching costs which can impede the productivity and fulfillment of workers.

While Plato may have been the first to stress the importance of matching people to jobs according to temperament and ability (Tinsley, 2000), the field of vocational psychology developed just over a century ago to research this important set of decisions. A pioneer in the study of vocational choice was Frank Parsons (1909) who outlined a tripartite model of career choice: (1) know yourself (in a variety of ways including abilities and preferences), (2) know your options (i.e., the characteristics of potential vocational paths), and (3) apply "true reasoning" to negotiate between the two. The first pillar grew from differential psychology which studies individual differences or the key psychological characteristics on which humans vary (Dawis, 1992). This includes research on the assessment of attributes like intelligence, personality, interests, and values through tests and surveys. The second pillar is exemplified by occupational taxonomies like the Dictionary of Occupational Titles (DOT; 1991) and the Occupational Information Network (O*NET; National Center for O*NET Development, 2020). In addition to describing the tasks which jobs in an occupational group tend to share, these taxonomies also characterize occupations in terms of psychological differences. This facilitates cleaner comparisons in the third step which underlies the key assumptions of person-environment fit research (Su et al., 2015). Literature in this domain supports the intuitive idea that matching a person's capabilities and preferences to the job will produce a host of favorable outcomes (e.g., better performance, less stress, and more satisfaction; Kristof-Brown et al., 2005).

Thus, individual differences are the foundation of vocational psychology. We know a great deal about what they are, how to measure them, and what they can predict. However, knowledge about how individual differences relate to one another and how they combine to predict valued work outcomes is still nascent. Cronbach (1957) draws an analogy between the

psychology of individual difference and the Holy Roman Empire in that people identify more strongly with their principality (e.g., personality or ability) than with a broader perspective. Each siloed domain investigates similar questions, but few theorists aim for thorough integration. Vocational psychology has not been immune to these silos:

> Extensive lines of research have emerged in relative isolation from one another in the areas of vocational interests, abilities, and personality characteristics; there has to date been relatively little systematic consideration of how interests, abilities, and personality characteristics interact to determine career choice… (Lowman, 1993, p. 550)

Lowman (1993) asserts that single domains cannot begin to capture the complexity of real people with real concerns and that assessing multiple constructs is essential for high-quality guidance. Nearly thirty years after his Inter-Domain Model of career assessment, relatively little has been done to integrate individual differences in vocational psychology. Broadly, the study of individual differences has splintered more and more over time and has likely prevented researchers from reaching new plateaus (Lubinski, 2000).

Of what value is integration though? Why should one take interest in the overlap of different types of attributes? In vocational psychology, Su et al. (2015) say that studying PE fit comprehensively requires inclusion of multiple individual difference domains. They mention an important and still unresolved question: what is the best way to combine these different domains in career counseling and assessment center situations? For people making career decisions, more thorough integration can inform which attributes to prioritize. For example, is it more important to look for a good match on verbal or spatial ability? Or is following one's passion and interests more important than either of those to achieve a fulfilling career?

More broadly, Ackerman (1997) offers several reasons to pursue integration of individual differences. For one, many major scientific advances come from combining two constructs previously thought to be conceptually or empirically orthogonal. He also points out that most all behavior is influenced by several traits simultaneously, and traits themselves are likely to develop interdependently over time. There are reliable correlations between individual difference domains (Ackerman & Heggestad, 1997), so studies limited to only one domain cannot estimate the relative importance of each nor can they demonstrate incremental validity of one over another. When substantive variables are omitted from a regression equation, this misspecification can bias parameter estimates for the surviving predictors (Nye, Butt, et al., 2018; Sackett et al., 2003). Similarly, isolated studies of, for example, the effects of value congruence on future job satisfaction are not only limited in predictive validity but they may also lead to incomplete or even inaccurate estimates.

The lack of integration may be affecting career counseling in practice. While data on which assessments career counselors actually use is limited, Watkins et al. (1994) found that vocational assessment is dominated by interest measures, the Strong Interest Inventory (Donnay, 1997) in particular, and that ability and personality measures are auxiliary. Even Spokane (1993), who claimed that counselors were already assessing and integrating multiple domains, recognized a strong focus on interest measures in career counseling (Spokane & Hawks, 1990) and an opportunity for greater use of ability measures. Chartrand & Walsh (2001) claim that good counselors do help clients synthesize results from different instruments, but they predicted that integrated reports from those assessments would become more popular. The dominance of interest inventories is perhaps unsurprising given their unique relevance to careers and career choices. However, personality and abilities may be underutilized, and it is possible that

counselors avoid other assessment domains because there is inadequate research on how to negotiate between them.

In addition to the lack of studies investigating multiple individual difference domains, there is also a lack of truly predictive studies. Not only are effect sizes likely to decrease with greater temporal separation of the predictors and criteria, but the pattern of the effects may change as well. For example, meta-analytic regression found that Extraversion, Emotional Stability, and Conscientiousness all related moderately and positively to job satisfaction (Judge et al., 2002). However, in a longitudinal study, the bivariate relationship between Conscientiousness and job satisfaction was roughly twice the magnitude of the other two, and its effect displaced the other two in a regression model (Judge et al., 1999). Thus, time can change the relative effects of individual differences in unexpected ways.

A key outcome variable in such prospective studies of vocational behavior is the degree to which people are satisfied with the career choices they make. Satisfaction with one's job or career is a more personal and proximal outcome than performance. That is, while young people making career decisions want to choose a path in which they are likely to excel, the probability of being satisfied with their careers (and the jobs that comprise them) is more personally relevant. While performing well in one's job relative to others can be intrinsically satisfying and can bring other valued outcomes like pay and status, those benefits can be rolled into the affective appraisal of one's job or career. While performance and satisfaction are relevant to both organizations and individuals, performance is more salient to organizations and satisfaction is more salient to individuals. Therefore, this study focuses on satisfaction for the sake of career choosers who want to optimize their own affective reactions to work. Unfortunately, PE fit studies examining the cumulative influence of multiple individual differences on satisfaction are

almost non-existent. One of the only studies to simultaneously examine the effects of interest, ability, and personality fit on job satisfaction focused on a relatively narrow, cross-sectional sample of two jobs in a vocational training context (i.e., Volodina et al., 2015). The current study examines all three of these content domains in a large, nationally representative, and longitudinal sample. In addition, most research over the years has operationalized fit in a single congruence index which sacrifices meaningful information and fails to account for the direct effects of person and environment characteristics. Edwards (1993) has made a compelling case for using polynomial regression to model fit. While direct effects account for the vast majority of variance in these studies, this method has shown promise, particularly when predicting attitudinal outcomes like job satisfaction (Yang et al., 2008). This study combines a robust sample with these modern analytical methods for analyzing fit.

The goals of this study are twofold. First, data on abilities, personality, and interests from a large sample of high school students are integrated empirically to map the nomological network of individual differences more thoroughly than most previous research has. The second and most central goal is to examine how each individual difference and its equivalent in the environment combines to predict Work Satisfaction using polynomial regression. To establish a conceptual foundation for these goals, this introductory section will (1) describe the three focal attributes and how they typically relate to one another, (2) discuss the person-environment fit paradigm and its relevance in studying satisfaction, and (3) outline predictions related to integration and the effects of PE fit on satisfaction.

Individual Differences

A nuanced understanding of the three individual differences is necessary to understand how they relate and how the different types of fit they produce can affect satisfaction. For

example, it is not enough to know the conceptual difference between intelligence and personality. The fact that one measures maximal performance while the other taps typical behavior has practical implications for integration. For each of the three individual differences, this section will highlight conceptual definitions, structure, measurement, and relationships with the other domains.

Cognitive Ability

The measurement of cognitive ability is one of the most productive and controversial domains of psychological research. On one hand, it may be the most consequential contribution from over one hundred years of psychology given its broad predictive validity. However, researchers still cannot agree on a single conceptual definition, some applications have been misguided and socially destructive, and lay conceptualizations often veer from scientific ones.

Definition, Structure, & Measurement. Cognitive abilities are "the latent constructs posited to account for correlated performances across different kinds of mental tasks" (Reeve & Bonaccio, 2013). Although abilities are not directly observable, most scholars agree that abilities are more than just statistical artifacts (Gottfredson, 1997). An ability must show some degree of temporal consistency, be measurable according to some objective standard of performance, and be relatively general such that it applies to multiple tasks (Jensen, 1998).

How many abilities are there? How are they related? Researchers have examined these questions about the structure of intelligence for over a century. Charles Spearman (1904) developed factor analysis which allowed empirical investigation of Francis Galton's hypothesized general factor of intelligence. He found support given that several broad abilities were significantly correlated and thus demonstrated positive manifold. Since then, some have denied the existence of a general factor and posited various types and numbers of mostly

uncorrelated abilities (e.g., Gardner, 2011). While Gardner's theory of multiple intelligences has wide, intuitive, and prosocial appeal, little to no evidence supports it (Waterhouse, 2006). Rather, mental abilities are reliably and significantly correlated across a range of different test batteries, factor extraction methods, and participant subgroups (Reeve & Bonaccio, 2013). Accumulated evidence has produced a relatively strong scientific consensus that mental abilities are hierarchically organized with a general factor, g, at the top. It should be noted, however, that credible and promising alternative explanations for positive manifold exist such as the dynamical hypothesis that uncorrelated specific abilities can mutually reinforce one another over time and, therefore, increase their correlation (van der Maas et al., 2006).

Given the potential importance of specific abilities, a brief review of prominent structural models follows. Cattell (1943) distinguished between fluid intelligence (g_f) and crystallized intelligence (g_c). Fluid intelligence is a basic reasoning or novel problem-solving ability while crystallized intelligence represents accumulated knowledge and skill. Fluid intelligence may be equivalent to g (Gustafsson, 2001) while crystallized intelligence likely develops as a result of applying one's g_f. Cattell's distinction between fluid reasoning and accumulated knowledge and skills is widely accepted and supported by neuroscientific evidence that fluid reasoning is associated with the pre-frontal cortex while crystallized intelligence is not (Blair, 2006). A student of Cattell's, John Horn, further refined the theory with nine abilities beneath g_f and g_c (Horn & Noll, 1997). Vernon (1961) posited two ability clusters under g: (1) *v:ed* or verbal:educational, and (2) *k:m* or spatial:mathematical. Carroll (1993) reviewed hundreds of datasets and emerged with eight narrow abilities that collectively subsume 69 specific abilities. Currently, the most prominent, comprehensive, and empirically validated model comes from McGrew's (2009) integration of prior work on the Cattell-Horn-Carroll (CHC) model which

maintains Carroll's g atop the hierarchy. Modern CHC competitors include the aforementioned dynamical model (van der Maas et al., 2006) and a descendant of Vernon's model which divides abilities into verbal, perceptual, and image rotation (VPR; Johnson & Bouchard, 2005). In general, the most commonly observed broad domains directly beneath g are verbal/linguistic, quantitative/numerical, and spatial/mechanical (Ones et al., 2017). Experts may never reach complete consensus on the structure of cognitive abilities, but that does not preclude the investigation and discussion of useful distinctions (Schneider & Newman, 2015).

Taking a general factor as given, what does this factor represent? What is intelligence? A widely cited definition comes from Gottfredson (1997) who attempted to articulate a scientific consensus:

> Intelligence is a very general mental capability that, among other things, involves the ability to reason, plan, solve problems, think abstractly, comprehend complex ideas, learn quickly and learn from experience. It is not merely book learning, a narrow academic skill, or test-taking smarts. Rather, it reflects a broader and deeper capability for comprehending our surroundings—"catching on," "making sense" of things, or "figuring out" what to do. (p. 13)

A more parsimonious definition might be abstract reasoning ability. Significant disagreement on a unifying verbal definition of intelligence remains, and some scholars have argued that the concept is too general to be useful. However, its conceptual utility may simply be its reference to a broad nomological network of inter-related cognitive constructs (Reeve & Bonaccio, 2013).

Considering what intelligence is *not* may clarify the definition further. In an effort to expand intelligence beyond the cognitive domain, scholars have posited Emotional Intelligence

(EI) as a broad ability that involves perceiving, understanding, and managing emotion as well as facilitating thought using emotion (Mayer et al., 2016). However, critics have challenged the classification of EI as an intelligence. For example, Locke (2005) allowed that intelligence, or the ability to grasp abstract concepts, can be applied to emotions (along with any other domain of human experience), but he asserted that those applications do not constitute separate types of intelligence. He suggested, and many scholars seem to agree, that what EI creators were actually describing is some collection of skills, habits, or choices related to emotion.

Measurement of the two constructs also demonstrates their differences. Cognitive abilities are typically measured via power tests which have correct and incorrect answers. These tests capture performance according to some objective and observable standard. Because of this, cheating can be a problem, but faking is not generally a concern as it is with self-report measures. These tests also measure maximal rather than typical performance (Cronbach, 1949). That is, cognitive ability tests capture peak mental performance ("can do") rather than actual sustained performance ("will do"). Unlike cognitive ability, the majority of EI tests are self-report. While ability measures of EI do exist (Mayer et al., 1999), questions remain about the objectivity of the answers (Matthews et al., 2004). Differentiating a newer construct like EI from intelligence is necessary to move forward with a sense of the concept's boundaries. In short, use of the term intelligence in this paper and in most other contexts (e.g., the eponymous journal) refers either to a broad network of related cognitive constructs or to the general latent factor of cognitive ability.

Given strong support for the existence of a general factor of intelligence, it can be tempting to ignore specific abilities. Indeed, the claim that such abilities account for little to no variance in performance beyond g is widespread (e.g., Hunter, 1986). However, there may still

be good reason to look below g (Reeve et al., 2015). Schneider & Newman (2015) list several potential advantages of a multidimensional view of intelligence. For example, they posit the compatibility principle which suggests that while general abilities predict general criteria, specific abilities may predict specific criteria, particularly when tailored to the context. They argue that the roughly 2% of additional variance in performance beyond g for which specific abilities account can have significant financial utility in employee selection. Nye et al. (2020) found even larger incremental R^2 values for specific abilities which were less correlated with g and tailored to the job tasks. Schneider & Newman (2015) also point to evidence that some specific abilities show less subgroup difference which can reduce adverse impact. Most relevant to this study, asymmetry in specific abilities (e.g., "ability tilt" is often operationalized as the difference between math and verbal abilities) can predict the domains in which people develop skills and succeed beyond g (Park et al., 2008), and higher ability levels are associated with more tilt. Not only do people who pursue STEM credentials have the highest ability levels overall, their spatial abilities tend to be higher than their verbal abilities while people pursuing non-STEM fields show the opposite tilt (Lubinski, 2010). Because different occupations emphasize, require, and select for different specific abilities, analyzing fit at that level of granularity has the potential to add nuance that g on its own cannot.

Personality

Personality is rare in PE fit literature, and when it is studied, it is typically operationalized as a form of person-organization fit (e.g., Bretz & Judge, 1994). In these P-O fit applications, meta-analysis suggests that the relationship with job satisfaction is significant but very small ($\rho = .08$; Bretz & Judge, 1994). Tinsley (2000) highlights the role of personality saying "Realization of the full potential of the P–E fit model depends on the elaboration of the

conceptual linkages between interest, needs, and values and the broader personality dimensions such as positive affectivity (extroversion)[*sic*], negative affectivity (neuroticism), and conscientiousness…" As work becomes increasingly collaborative and team-based, PE fit in the domain of personality will likely become even more important (Chartrand & Walsh, 2001).

Definition & Structure. Funder (1997) offers one of the more intuitive definitions of personality as "an individual's characteristic patterns of thought, emotion, and behavior, together with the psychological mechanisms–hidden or not–behind those patterns." Most psychological research has focused on describing the "characteristic patterns" rather than theorizing and testing "mechanisms". The separation is important given that while personality is substantially heritable, there is no reason to assume that our frameworks for making sense of manifest personality correspond to causes like brain structure or psychophysiology (Saucier & Srivastava, 2015).

A definitive difference between intelligence and personality is that the former is an ability while the latter is a trait. Both are latent characteristics inferred from observed behavior, but abilities are evaluated in relation to a standard of performance whereas personality is less normative and more concerned with how an individual typically thinks, feels, and behaves rather than what she or he is maximally capable of doing.

By far, the dominant model of personality is the Five Factor Model (FFM) or the Big 5. While researchers have proposed various names for the factors, the most popular to date are (1) Extraversion, (2) Agreeableness, (3) Conscientiousness, (4) Neuroticism, or Emotional Stability in reverse, and (5) Openness to Experience. These are listed in the order in which the factors are typically extracted. Scholars typically recognize that personality is hierarchically organized (Judge et al., 2013). The exact levels of organization are less clear, but proposed levels typically include the following in order from most to least general: one general factor, two meta-traits, five

factors, ten aspects, various configurations of facets, and some have even argued for nuances which are individual items (Mõttus et al., 2017). This study focuses only on the two meta-traits, five factors, and ten aspects because they have satisfactory empirical support and they represent a useful balance between general and narrow.

There is disagreement on the validity of these structures within and between levels, but the FFM factors are the most widely accepted in the hierarchy. The five factors emerged through decades of research based on the lexical hypothesis. This assumes that descriptions of human variation which are highly represented in natural language are likely to be most socially important (Allport, 1937). Broadly, personality psychologists operating under this hypothesis would gather large collections of descriptors, ask people to rate themselves or others on those descriptors, and then use factor analysis to decipher underlying dimensions. In practice, researchers may have piggy-backed on the lexical simplifications of their predecessors at times creating an illusion in hindsight that the FFM emerged without bias (Block, 1995). Nonetheless, most scholars recognize the utility and replicability of the five-factor model.

This relative consensus has not prevented competition. The HEXACO model is perhaps the most popular alternative to the FFM (Ashton & Lee, 2007). It adds a sixth Honesty/Humility factor and alters the existing Agreeableness and Neuroticism factors. No structure with more than six factors has been replicable (Saucier & Srivastava, 2015). A wide variety of personality traits have been conceptualized outside of any taxonomy. While many can certainly lend incremental validity, many can be at least partially explained as compound traits which combine elements from the FFM trait hierarchy (Stanek & Ones, 2018). At this point, anyone proposing a new personality trait should demonstrate that it explains unique variance beyond the FFM or conceptualizes the trait in a more useful way.

Meta-Traits. Empirically, the factors in the FFM are not orthogonal. They delineate fuzzy boundaries which show noticeable and stable patterns of correlation between the factors. One regularity is that Agreeableness, Conscientiousness, and Emotional Stability tend to correlate positively. Digman (1997) identified this constellation as factor alpha (α) while DeYoung (2006) developed it theoretically and renamed it Stability. Thus, these three traits represent three separate forms of stability: (1) relational, (2) motivational, and (3) emotional. The remaining two traits in the FFM (Extraversion and Openness to Experience) form a second higher order factor called factor beta (β) or Plasticity. This meta-trait represents something like social, intellectual, and experiential exploration. Differences in serotonergic function may account for some of the variance in the Stability meta-trait while dopaminergic function may correspond to Plasticity (DeYoung et al., 2002). Stability and Plasticity may be analogous to the colloquial uses of character and personality respectively (e.g., "She has personality"; Saucier & Srivastava, 2015).

Five-Factor Model & Aspects. The factors in the FFM are narrower than meta-traits, and each of the five factors subsumes two lower-order factors known as aspects. Extraversion is primarily associated with sensitivity to rewards such that more extraverted people tend to exhibit stronger brain activity when presented with rewards (Connelly et al., 2018). There are two main types of rewards that help differentiate between the two aspects of Extraversion. Incentive or appetitive rewards occur during the pursuit of valued outcomes (i.e., enjoyment of the means) while consummatory rewards occur upon success (i.e., enjoyment of the ends). Appetitive rewards are associated with the Assertiveness aspect which subsumes the dominance and activity personality facets. Consummatory rewards are associated with the Enthusiasm aspect of personality which subsumes the facets of sociability and positive emotion. Agreeableness is

broadly associated with a "willingness to coordinate goals with others" (Connelly et al., 2018) with the low end representing pure self-interest. It is further split into Politeness and Compassion which are cognitively and emotionally oriented respectively. Conscientiousness is most directly goal-oriented, as it involves self-regulation of behavior in the protection of long-term goals. The Industriousness aspect involves focus and hard work toward the achievement of goals while the Orderliness aspect involves rule-adherence, cleanliness, and meticulousness. Neuroticism is mostly characterized by negative emotion. It is generally associated with threat sensitivity, avoidance, and defensiveness. The Withdrawal aspect of Neuroticism constitutes more passive avoidance while the Volatility aspect is more active. Openness influences how much information one considers in goal pursuit and how deeply one processes it. The Intellect aspect is intertwined with cognitive ability, and it is associated with intellectual engagement and creativity. The experiential aspect of Openness, labelled Openness to Experience, is more related to sensory experiences like aesthetics and emotions.

Measurement. The vast majority of personality tests are questionnaires with most being self-report. Projective tests like the Rorschach inkblot test have been largely discredited and supposedly objective tests like the Implicit Association Test have little evidence of validity (Paunonen & Hong, 2015). While self-report questionnaires are typically the best option available today, they have several problems. These include the fact that people might not be consciously aware of exactly what determines their behavior. A good deal of our own reports might be post-hoc justifications. Additionally, memory of behavior is far from perfect, and asking people to aggregate their behavior over a long timeline is even more problematic. Lastly, people can intentionally misrepresent themselves (e.g., impression management, socially desirable responding), and some scenarios may incentivize this (e.g., employee selection

situations). However, response distortion can be mitigated by using neutral wording, forcing choices between equally desirable options, or simply telling people to be honest.

Personality & Intelligence. Before reviewing specific intelligence-personality associations (IPAs), one must consider how these associations are studied. Because ability and personality are measured differently (i.e., power tests vs. surveys), there is little concern that common method bias will inflate correlations. However, more "typical" measures like self-reported ability and intellectual engagement have proven valuable, and those measures could produce such a bias. There is evidence that personality measures are understood well by most participants and invariant across ability levels (Waiyavutti et al., 2012), but some scholars have questioned whether ability level might influence how participants respond to personality questionnaires. Overall, research on the association between intelligence and socially desirable responding is mixed. For example, Levashina et al. (2009) found evidence that more intelligent people were less likely to fake responses to a biodata measure, but when they did fake, they were able to inflate their scores even more than low ability participants.

Openness. The relationship between Openness to Experience and general cognitive ability is the most studied IPA. Two meta-analyses have found the correlation between the two to be .33 (Ackerman & Heggestad, 1997; Judge et al., 1999). This correlation is substantial, particularly given that the two constructs do not share a common method of measurement (DeYoung, 2015). Furnham & Cheng (2016) found that childhood intelligence (measured at age 11) predicted Openness in adulthood (age 33) more effectively than parental social class, school motivation, education, or adult occupation. Indeed, there seem to be some reciprocal relationships between Openness and g_f, and both predict future g_c (Ziegler et al., 2012).

There are at least two important caveats to this broad effect size. First, crystallized intelligence accounts for the majority of the relationship, as the correlation between fluid intelligence and Openness is much lower (Goff & Ackerman, 1992). To the extent that trait Openness drives learning and new experiences, it seems rather intuitive that these people would accrue more knowledge and skills. Second, the Openness to Ideas facet in the NEO-PI-R (Costa & McCrae, 1992) or the Intellect aspect (DeYoung et al., 2007) account for most of the covariance as opposed to facets like Openness to Fantasy, Aesthetics, Feelings, or Values. Even for Openness-g_f relations, which are typically low, Openness to Ideas explains most of the overlap (Moutafi et al., 2006) . Some researchers claim that intellect, Openness to Ideas, and even related constructs like Typical Intellectual Engagement (TIE; Goff & Ackerman, 1992) and need for cognition (Cacioppo & Petty, 1982) function as self-report, typical (vs. maximal) measures of ability. Brand (1994) even proposed that g be incorporated into personality to form a "Big 6". Regardless, it appears that the more cognitively oriented form of Openness is what covaries with performance on cognitive ability tests. Rather than Openness being a consequence or a self-report measure of intelligence, the most plausible explanation is that Openness determines one's level of intellectual investment (via interests and curiosity) which then influences accrual of crystallized intelligence (e.g., investment via TIE; Chamorro-Premuzic & Furnham, 2005; von Stumm & Ackerman, 2013).

Emotional Stability. Emotional Stability tends to correlate positively with intelligence (Rammstedt et al., 2018), and it seems that anxiety accounts for most of the deleterious effects of Neuroticism on ability (Ackerman & Heggestad, 1997). Based on available evidence, it seems more likely that Neuroticism relates to worse test performance via test anxiety rather than neurotic people actually being less intelligent (Chamorro-Premuzic & Furnham, 2005). Indeed,

state anxiety is significantly more predictive of test performance than trait anxiety (Zeidner, 1995).

Conscientiousness. Some studies have found negative correlations between Conscientiousness and intelligence. Some have endorsed an intelligence compensation hypothesis that people with lower abilities might feel a need to work harder (Moutafi et al., 2004). However, it is possible that negative relationships are due to range restriction or the use of relatively high-achieving samples. For example, Murray et al. (2014) found that less restricted samples (e.g., including students with low GPAs) show either zero or positive correlations between Conscientiousness and intelligence. However, Rammstedt et al. (2016) controlled for education and still found a negative relationship between Conscientiousness and verbal and numerical abilities. Further research is necessary to determine whether prior negative correlations are substantive, due to range restriction, or due to a confounding third variable.

Extraversion. In general, correlations between Extraversion and intelligence have been mixed and small (Zeidner, 1995). In the 1980s, arousal theorists hypothesized that extraverts seek more stimulation, and therefore, may perform better on tests with time pressure, but this effect has failed to replicate (Chamorro-Premuzic & Furnham, 2005). Ackerman & Heggestad (1997) found that intelligence and specific abilities tended to correlate with two broad categories: (1) intellectually oriented traits like Openness and TIE (a well-established finding), and (2) traits related to Extraversion and positive emotionality. Later, Wolf & Ackerman (2005) found that correlations between Extraversion have decreased over time which may be due to changing measurement preferences (e.g., a transition from Eysenckian Extraversion to NEO-PI-R Extraversion). However, they also confirmed that effect sizes are negligibly small in general.

Agreeableness. One of the least studied personality correlates with intelligence is Agreeableness. There are several hypotheses about how Agreeableness may influence ability tests (e.g., the modesty facet reflects an accurate self-assessment of lower ability, agreeable people will try harder on tests for research purposes which have little potential for personal gain; Chamorro-Premuzic & Furnham, 2005). In general, however, the effects are mixed and negligible, and there is little theoretical reason to expect Agreeableness to have a long-term substantive relationship with intelligence or knowledge accrual.

Vocational Interests

A broad definition of personality (e.g., Guilford, 1959) might subsume interests. Indeed, the dominant model of interests is often conceptualized as personality types or constellations of work-related traits (Holland, 1973). Both attributes are motivational in the sense that "they influence choices individuals make about which tasks and activities to engage in, how much effort to exert on those tasks, and how long to persist with those tasks" (Mount et al., 2005). However, most scholars adopt a more restricted definition of personality and interests and choose to separate them conceptually (Ackerman, 1997). While there are stable correlations between the two domains, the magnitudes are not strong across dimensions, and many inter-domain correlations are near zero. They are conceptualized and measured differently such that while personality focuses more on typical behavior, interests focus on preferences for particular activities or circumstances.

Strong (1943) analogized interests as the rudder of a boat and abilities as the motor. Interests set the direction while abilities dictate how fast one can move toward the target. However, disciplines diverge when choosing how long the journey is. Education researchers typically conceptualize interest as an affective state associated with positive mental engagement

with the subject matter and an approach orientation. Silvia (2008) proposed two preconditions for the emotion of interest to occur: a stimulus must be (1) new (i.e., outside the realm of prior knowledge and skills) and (2) comprehensible (i.e., not so far outside of one's knowledge and skills that it cannot be managed or conquered). A student's moment-to-moment interest (or lack thereof) is consequential because it can increase persistence, depth of studying, memory, and performance. In contrast to the educational and affective perspectives, vocational and organizational psychologists typically view interest as a stable, trait-level individual difference (Su, 2018). This paper focuses on interests at the trait level rather than the situational interests studied in the education literature.

Definition & Structure. Hansen & Wiernik (2018) discuss vocational interests within the broader context of work preferences which they define as "enduring individual differences in attraction to or liking of particular aspects of work." They define vocational interests in particular as

> …individuals' characteristic patterns of preferences for certain work activities and work environments. Interests are described in terms of how appealing or engaging an individual finds certain activities (e.g., writing), topics (e.g., science), environments (e.g., outdoors), or ways of working (e.g., alone vs. in a team). (p. 409)

Holland's (1973) theory of vocational types has dominated the vocational interest paradigmatically even more than the FFM have in personality research. This dominance is due partially to the development and proliferation of theory-concordant measures (Nauta, 2010). Similar to the FFM, another reason for its popularity is its intuitive appeal and ease of application. Holland's RIASEC model includes six interest types: (1) Realistic, (2) Investigative, (3) Artistic, (4) Social, (5) Enterprising, and (6) Conventional. Realistic jobs emphasize

mechanical, agricultural, and technical skills. Investigative jobs are scientific and intellectually oriented. Artistic jobs are unstructured and emphasize creativity. Social jobs involve helping, teaching, and working with others. Enterprising jobs involve leadership and persuasion. Lastly, Conventional jobs are often clerical and involve working in highly structured and routinized systems. These six interests are arranged in this order in a circumplex structure implying that interests closer to one another (e.g., Investigative and Artistic) will be more empirically correlated while interests farther from one another (e.g., Realistic and Social) will be less or negatively related.

The circumplex structure of the RIASEC model has empirical support (Tracey & Rounds, 1993) with some caveats. First, the interests are not evenly spaced in a perfect hexagonal structure (Holland & Gottfredson, 1992). Second, while the circumplex structure does account for some of the interrelations between RIASEC interests, individual scale scores retain unique variance for which the circumplex cannot account (Hansen & Wiernik, 2018). Third, Holland's six dimensions are not sacred (Tracey & Rounds, 1995). More or fewer dimensions can describe the circumplex adequately, and the appropriate level of abstraction may depend on the application. Given these caveats, more research on basic interests (analogous to personality facets) is valuable and needed. At more general levels, Prediger (1982) posited that the two dimensions underlying the circumplex were a general focus on People vs. Things (forming an axis from Social to Realistic interests) and Data vs. Ideas (forming an axis that bisects Enterprising-Conventional on one end and Investigative-Artistic at the other). A relabeling of the Data vs. Ideas dimension to Structured vs. Dynamic has been proposed to be more general or inclusive (Armstrong et al., 2004). Hogan (1983) rotated these dimensions 30 degrees to the right forming Sociability and Conformity dimensions. While Prediger's dimensions are more widely

used, Tokar et al. (1995) found two dimensions supporting those found by Hogan. In addition, Hogan's dimensions seem to overlap more intuitively with personality variables (Armstrong et al., 2013). The remaining 30-degree rotation appears in a variety of studies as well (e.g., Ackerman et al., 1995), so deciphering the "true" underlying dimensions may be unlikely or of questionable use. In some research, a third dimension emerges which Tracey & Rounds (1996) called Prestige, but may be more appropriately labelled Complexity (Hansen & Wiernik, 2018). Additionally, while propositions about underlying dimensions assume bipolarity, low negative correlations between opposite poles suggest that each pole should be considered as an independent factor (Tay et al., 2011).

Measurement. In general, interest inventories assess one or more of the following preferences: general themes at the level of Holland's RIASEC domains, basic interests which are more specific, or occupational interests which are the most specific (e.g., to what extent are the test taker's interests aligned with satisfied members of a particular occupation). Some inventories also ask participants to report on their skills (Self-Directed Search; Holland, 1994) or personality (Strong Interest Inventory; Donnay, 1997), but these sections should be considered ancillary rather than interest measures per se.

Hansen & Wiernik (2018) argue there is no reason to expect a measure geared toward career exploration to be equally valuable for prediction, and they recommend developing targeted measures. They point out that the Self-Directed Search focuses on Summary Codes which are typically the participant's top three general interest domains. While this convention may be helpful to an individual client, it is generally less useful for prediction when it sacrifices information. For this reason, the current study focuses on scale scores and the broader profile of all six interest dimensions.

Interests & Intelligence. In general, intelligence-interest associations are small to moderate. In a meta-analysis, Pässler et al. (2015) found that the largest relationships with g were Investigative ($\rho = .28$), Realistic ($\rho = .23$), and Social ($\rho = -.19$) interests. The strength and direction of the coefficients were similar across genders with the minor exception that Realistic interests may be more closely related to g for women. While based on a relatively small number of studies, intelligence-interest correlations were higher in adults (i.e., above 20 years old) than children. Also, specific abilities showed differential patterns of correlation with interests. For example, Investigative and Realistic interests correlated with spatial and quantitative abilities while Artistic and Investigative interests are associated with verbal ability. In the spherical representation of interests (Tracey & Rounds, 1996), the third dimension of Prestige or Complexity correlates with verbal and quantitative abilities (Armstrong et al., 2008). These abilities fit in what Stanek & Ones (2018) label "Acquired Knowledge". In a multidimensional scaling procedure, written comprehension, written expression, mathematical reasoning, and numerical facility vectors pointed toward greater complexity and clustered around Investigative interests (Armstrong et al., 2008).

Interests & Personality. Openness is correlated most strongly with Artistic interests ($\rho = .41$; Mount et al., 2005), but it also shows reliable covariance with Investigative interests ($\rho = .25$). Extraversion correlates with Enterprising ($\rho = .40$) and Social interests ($\rho = .29$) while Conventional interests may correlate with Conscientiousness ($\rho = .19$). These five relationships have significant precedent and appear highly replicable (Costa et al., 1984; Gottfredson et al., 1993; Larson et al., 2002). In addition, Social interests may have a weak to moderate association with Agreeableness. Additionally, Sullivan & Hansen (2004) provided preliminary evidence that lower-order facets may explain these associations more accurately

(e.g., the Assertiveness facet of Extraversion accounts for that trait's association with Enterprising interests).

Hogan's (1983) Sociability dimension is related to Extraversion while the Conformity dimension is related to Openness (negatively; Armstrong & Rounds, 2010). Conscientiousness may also relate somewhat positively to the Conformity dimension. Perhaps unsurprisingly, person-oriented interests are more highly related to personality variables (Barrick et al., 2003) while Realistic and Investigative interests have little association with personality (De Fruyt & Mervielde, 1997). Given that Realistic and Investigative interests account for most of the association between interests and intelligence, it appears that personality and intelligence account for separate halves of the interest circumplex. It should be noted, however, that examining personality profiles (i.e., intraindividual levels) rather than absolute values has explained variance even in Realistic interests (Wiernik, 2016), and the practice shows promise for elucidating personality-interest relationships.

The FFM aspects may illuminate personality differences between RIASEC domains. For example, while Extraversion is associated with both Enterprising and Social interests, the Assertiveness aspect is more closely associated with Enterprising interests while the Enthusiasm aspect is more closely related to Social interests (Sullivan & Hansen, 2004). Similarly, Openness to Ideas has a stronger relationship with Investigative interests whereas other facets of Openness are associated with Artistic interests.

Some have argued that vocational interests are just the manifestation of personality at work (e.g., McCrae & Costa, 1990). However, interest researchers maintain that interests reflect fundamental ways of relating to our environments (Rounds & Su, 2014). Several pieces of evidence support at least some independence of interests from personality: (1) the correlations

between personality and interests are modest, (2) interests stabilize earlier in life than personality, and (3) interests show significant genetic variance for which personality does not account (Kandler et al., 2011). In addition, interests and personality have formed two distinct clusters in multi-dimensional scaling analyses (Mount et al., 2005). As previously mentioned, an intermediate theory suggests that interests arise from personality profiles like recognition of and capitalization on cardinal strengths (Dilchert, 2007).

Integration

The preceding section on the three focal individual differences and their relationships serves as a theoretical and empirical backdrop for this study. In particular, the first goal of this study is to identify patterns of association between the various factors in these three domains and map their nomological network. What follows is a brief review of key pieces of integrative research that move beyond simple, bivariate, inter-domain relationships and into more thorough methods of integration that begin to map the territory of individual differences simultaneously into one cohesive picture.

The following integrations are primarily empirical, but theorists have constructed various explanations of inter-domain relationships. For example, Ackerman (1996) posited that abilities and personality influence a person's likelihood of success in a particular activity, and people are more likely to develop interest in activities in which they do well. This, in turn, leads to greater investment in that activity and greater accumulation of knowledge or crystallized intelligence related to it. Similarly, Krauskopf (1998) emphasized the causal potency of abilities on personality through the tendency to prefer behaviors which align with preexisting strengths.

Ackerman & Heggestad (1997)

Cattell (1943) emphasized the importance of considering multiple characteristics and identifying their unique contributions via multiple regression when trying to understand psychological phenomena. Later, Snow (1978) suggested there may be value in examining what he called aptitude complexes or clusters of related traits of varying types.

A seminal article illustrating this approach came from Ackerman & Heggestad (1997). They reviewed and meta-analyzed associations between intelligence, personality, and interests, and they identified four trait complexes. Each complex represents a cluster of traits that all tend to correlate reliably with one another (based mostly on correlations of .20 or higher), not mutually exclusive categories or types. The four complexes included the following constructs relevant to this study: (1) *Social*: Enterprising and Social interests along with Extraversion; (2) *Clerical/Conventional*: Conventional interests and Conscientiousness; (3) *Science/Math*: Realistic and Investigative interests along with math reasoning ability; (4) *Intellectual/Cultural*: investigative and Artistic interests along with g_c and Openness. These clusters reflect many of the inter-domain associations described earlier (e.g., the associations between Openness, g_c, and Investigative and Artistic interests).

Note that all four complexes have defining interests, and the complexes even mirror the hexagonal RIASEC structure. However, the Social complex has no ability associations, and the only ability in the Clerical/Conventional complex is perceptual speed which is typically least related to broad measure of intelligence (Ackerman, 2003). Conversely, the Science/Math complex has no personality traits, and the Intellectual/Cultural complex includes primarily intellectually oriented personality traits (Typical Intellectual Engagement, Openness, and Absorption). Ackerman (2018) frames this finding as an opportunity to discover both social

abilities and scientific personalities. For example, the construct validity and measurement of emotional, social, or interpersonal intelligences is still questionable. However, such a constellation of abilities would almost certainly land in the Social trait complex. Different and more sophisticated measurement techniques may be required to capture such abilities. Conversely, more research could investigate whether our dominant models of personality are deficient for describing individuals in the Science/Math complex.

Trait complexes like those in Ackerman & Heggestad (1997) and other trait aggregations have several potential uses. First, while using fewer predictors can sacrifice information and hinder prediction (e.g., Major, 2013), there is evidence to suggest that matching predictors and criteria on their level of generality can improve predictions (Ones & Viswesvaran, 1996). Second, identifying reliable clusters can help with theory development. Ackerman (1997) describes the complexes as "sets of traits that are sufficiently interrelated to suggest exploration of mutually causal dependencies." After determining that correlations between two traits are not due solely to similar item content, he recommends building and testing theory about the mechanisms which might cause both traits or create reciprocal causation between them. Lastly, if such trait complexes replicate reliably, they can guide development of compound trait measures which can tap the construct space more efficiently. For example, it may be fair to categorize a variety of individual difference variables as combinations or profiles of more foundational variables. Stanek & Ones (2018) present a collection of variables with corresponding FFM profiles (e.g., trust may be seen as high Agreeableness combined with low Neuroticism), and Ones & Viswesvaran (2011) highlight the utility of integrity tests which are compound measures.

Armstrong & Colleagues

Unlike Ackerman & Heggestad (1997) whose inductively derived trait complexes just happen to include all six interests, Armstrong et al. (2008) chose a priori to use the circumplex structure of interests as a baseline framework for integration. That is, the circular RIASEC structure was used as a set of standard reference points on which other traits could be mapped. Rooted in the reciprocal development of interests, personality, and ability that the socioanalytic model of identity development outlines (Hogan, 1983), their integration hypothesizes that the three characteristics should coalesce in adult populations and form trait constellations.

The study by Armstrong et al. (2008) is part of a stream of research that utilizes multidimensional scaling (MDS) and property vector fitting. The former may be preferable to factor analysis when correlation matrices show a circumplex structure as the RIASEC does. Guttman (1954) pointed out that multidimensional scaling of ability tests would place tests of the same ability in straight lines extending from the origin. Further, a test's distance from the origin would indicate its level of specificity (i.e., points closer to the origin are more general and, in the case of cognitive ability, have higher g loadings). Property vector fitting uses regression weights to derive coordinates for plotting in a multidimensional space. Vectors emerging from the origin have a bidirectional interpretation: the direction of the vector indicates its mean positive correlation while the opposite direction implies a weak or negative correlation. Higher values of R^2 indicate that the external variable fits well in the RIASEC circumplex.

Most of the bivariate relationships reviewed earlier in the present paper held in Armstrong et al. (2008) at both the individual and occupation levels. Male and female vectors for Extraversion landed between Enterprising and Social interests, Conscientiousness vectors landed between Conventional and Enterprising interests, and Openness vectors pointed toward Artistic

interests. They also plotted environmental demands in the RIASEC circumplex. As Ackerman & Heggestad (1997) found, most of the cognitive abilities pointed toward Investigative and Realistic interests while none pointed toward Enterprising or Social interests. Some more creative abilities like Fluency of Ideas pointed toward Artistic interests. Lastly, Armstrong et al. (2008) located interests empirically with multidimensional scaling to identify three underlying dimensions. The first two mapped the typical RIASEC circumplex, and the third represented a cognitive complexity dimension with all cognitive ability vectors pointing toward the high complexity dimension.

Mount et al. (2005)

Lastly and most germane to this study, Mount et al. (2005) used hierarchical clustering on meta-analytic data to decipher the structure of personality and interests when considered simultaneously. This replicated the personality meta-traits (α & β) given that Extraversion and Openness formed a cluster before joining with a cluster formed by the other three personality traits. Interests also clustered before joining as a domain such that R-I, A-S, and E-C formed the first clusters. Only after forming two clusters between domains did interests and personality join at the top of the hierarchy. While common method bias is a possible explanation for the separation between domains, the authors argue that the inclusion of a variety of measures in each domain and the separation of factors α & β suggest that at least some of the separation is substantive.

This study also used multidimensional scaling to identify three higher-order dimensions that combined both personality and interests. MDS maps the relationships between constructs such that more highly correlated variables lie physically closer to one another in multidimensional space. Those dimensions are akin to factors in factor analysis such that they

can reduce the dimensionality of the data and make sense of the higher-order organization of many different constructs. The first dimension in Mount et al. (2005) separated the two domains of personality and interests as clustering did. They also revealed that factor β was closer to interests than factor α which is consistent with the notion that interests are about growth and learning. Dimensions two and three replicated Hogan's (1983) Conformity and Sociability dimensions, respectively. That is, the first dimension was defined by Conventional interests and Conscientiousness on one end and Artistic interests and Openness to Experience on the other. The third dimension had Investigative and Realistic interests on one end and Extraversion, Enterprising, and Social interests on the other. Because the conformity dimension combines with Conscientiousness, the authors conceptualize this dimension as striving for achievement vs. striving for personal growth. It is possible that analyzing interests along with personality variables shifts the focus away from Prediger's (1982) People-Things and Data-Ideas dimensions and toward Hogan's more personality-congruent dimensions.

Hypotheses

MDS is well-suited to mapping individual differences in this study for two main reasons. First, in comparison to a correlation network plot which essentially just reproduces a correlation matrix visually, MDS represents both bivariate relationships between constructs and dimensions that may undergird those relationships. Second, as mentioned previously, because domains like the RIASEC have a predictable circumplex structure of intra-correlation, MDS is recommended over factor analysis for identifying those dimensions. By including ability factors as a third domain, the current study expands on the multi-dimensional scaling approach used by Mount et al. (2005) which only included personality and interests. Those authors note that while the FFM and the RIASEC are well vetted models of those domains, the results could have been different if

data came from other classification schemes. The current study explores this possibility by using personality and interest inventories uninformed by either the FFM or the RIASEC. If the pattern of results in this study is similar to those in Mount et al. (2005), one can have a higher degree of confidence that the pattern is substantive and not simply an artifact of the measurement models chosen. Beyond this expansion, the higher-order dimensions identified with MDS could be used as predictors of job satisfaction. Because individual difference domains typically show moderate levels of both intra- and intercorrelation, collinearity may be a concern. Therefore, identifying composites could reduce the complexity of the model, reduce the standard errors of the estimates, and potentially help with interpreting results at a higher level of abstraction.

Overall, personality and interests show higher associations with each other than they do with abilities. Instead of representing what a person can do, these constructs are concerned with preferences or what a person is likely to do. In this sense, they are more similar conceptually. Indeed, Holland (1973) originally conceptualized interests as elements of personality. Both constructs are also most commonly measured via self- or other-reports rather than the power tests that are used to assess abilities. This common method may account for some of the stronger relationships between personality and interests. However, their conceptual similarity remains, and the strong relationship between, for example, Openness and abilities or Investigative interests and abilities shows that constructs which do not share a measurement paradigm can still associate reliably when they are theoretically linked.

While the first and most significant dimension found by Mount et al. (2005) separated personality and interests, including abilities in these analyses is likely to change that. Because personality and interests are more similar to one another than they are to abilities, the first and

most important dimension identified in a multi-dimensional scaling analysis is likely to separate abilities and non-abilities:

H1a: Personality and interest constructs will be more similar to one another (i.e., physically closer in Euclidean distance) on average than either will be to abilities.

In MDS, the order in which dimensions are extracted matters. As in principal components analysis, the first dimension extracted accounts for the most variance in the data, the second accounts for the next most, and so on. Given this, hypotheses about the relative importance of the extracted dimensions can be formulated in advance. While the first and most important dimensions found by Mount et al. (2005) were disintegrative in that they separated individual difference domains, subsequent dimensions were integrative (i.e., they incorporated multiple domains on the high and/or low ends). In this study, including abilities should affect both the disintegrative and the integrative dimensions. Because abilities relate more closely to Investigative and Realistic interests than to Social or Enterprising interests, the sociability dimension (which bisects Enterprising and Social interests at the high end and Realistic and Investigative interests at the low end) may become more important than the conformity dimension (which runs from Conventional interests on the high end to Artistic interests on the low end). That is, the sociability dimension will explain more variance than the conformity dimension and will therefore be extracted before it in a multi-dimensional scaling model. The first integrative dimensions should correspond to Hogan's (1983) hypothesized dimensions.

H1b: In contrast to the findings in Mount et al. (2005), adding abilities will cause the sociability dimension to account for more variance than the conformity dimension.

Person-Environment Fit

> *Of all of the issues in psychology that have fascinated scholars and practitioners alike none has been more pervasive than the one concerning the fit of person and environment.*
>
> – Benjamin Schneider (2001)

As mentioned previously, research on the negotiation between person and environment can be traced back to Parsons (1909). Since then, researchers have elaborated on the underlying theory in person-environment fit research. Holland (1973) argued that the RIASEC model of vocational personalities could be applied to environments as well. From this, he proposed a congruence hypothesis that when the vocational interests of employees matched the characteristics of the environments in which they worked, employees would flourish. He conceptualized the environment as the aggregated profiles of the people who make up that environment. This is in line with Schneider's (1987) claim that "the people make the place." In person-environment fit research, this concept is most closely aligned with supplementary fit (Muchinsky & Monahan, 1987). When an employee is similar to other people in their environment, supplementary fit is high. This study focuses exclusively on this view of fit endorsed by Holland and Schneider.

In contrast, complementary fit occurs when a "weakness or need of the environment is offset by the strength of the individual, and vice versa" (Muchinsky & Monahan, 1987). Rather than just being similar, one entity provides what the other wants. The Theory of Work Adjustment (TWA; Dawis & Lofquist, 1984) presents a PE fit theory that focuses primarily on complementary fit. Complementary fit can be further subdivided according to the direction of need-fulfillment. For example, needs-supplies fit (NS fit) is the degree to which the environment can satisfy a person's needs, goals, values, interests, or preferences (Cable & DeRue, 2002;

Tinsley, 2000). In contrast, demands-abilities fit (DA fit) is typically conceptualized as the degree to which a person is capable of fulfilling the demands of a role. This distinction is not only conceptual: empirical studies suggest that the two types of complementary fit have different effects on outcomes (Edwards & Shipp, 2007). Additionally, these three constructs do not appear to be simply different manifestations of a broader, overall fit construct (Badger Darrow & Behrend, 2017; Edwards & Billsberry, 2010). The Theory of Work Adjustment stipulates that workers are satisfied when environmental reinforcers (e.g., pay, prestige, working conditions) meet workers' needs. Conversely, workers are satisfactory when they can meet the demands of the job through their human capital (i.e., knowledge, skills, abilities, etc.). The theory also proposes that satisfactoriness and satisfaction can moderate one another (e.g., workers who can meet the needs of their environments will be more satisfied with the work) and that other traits beyond an individual's needs and skills can moderate these relationships (e.g., personality and interests).

The environment to which an individual is compared can be conceptualized in a variety of ways as well. Studies have measured the supplies and demands of organizations, vocations, jobs, work groups, supervisors, and coworkers. Again, different levels have different effects on outcomes, so this distinction is important. Because this study focuses on career choice, the most relevant type of fit is person-vocation fit or the extent to which people fit with a broad occupational group rather than any specific job or organization within that group. This level of analysis is more relevant to early career decisions which are more likely to focus on broad themes over narrow instantiations.

Fit can also be measured directly or indirectly. Direct fit assessments (a.k.a. perceived fit) ask people to report directly on their perception of their own fit with the environment. This

encompasses molar fit (perceived fit between P and E) and molecular fit (perceived discrepancy between P and E; Edwards et al., 2006). Indirect fit measurements which compare separate ratings of P and E are atomistic, and they can be either subjective (i.e., compare a person's self-rating on some attribute to that same person's rating of the environment on that attribute) or objective (i.e., compare self-ratings to external ratings of the environment). While all three of these strategies aim to measure the same underlying construct, they are distinct facets which can produce very different results in terms of prediction (Cable & Judge, 1997). This can happen because people weigh dimensions within broader fit constructs in unique ways or because people are motivated to maintain cognitive consistency between, for example, their NS fit ratings and job satisfaction ratings (Kristof-Brown et al., 2005). Associating perceived fit and job satisfaction is particularly vulnerable to common method bias (Podsakoff et al., 2003) which is problematic in studies examining attitude-attitude relationships. Thus, while perceived fit relates to satisfaction more strongly than objective fit, the former relationship is likely inflated due to construct overlap and common method variance. This study attempts to sidestep these issues by focusing on objective, atomistic fit (i.e., environment ratings are external to the individual). This operationalization is most useful for early career decisions in which people who have little to no work experience must rely on external descriptions of different environments and speculate on how to achieve the best fit.

Lastly, and most relevant to the current study, PE fit can be conceptualized across different content domains (Edwards & Shipp, 2007). Many fit studies focus on a particular domain like values fit or interests fit. A more gestalt approach examines global fit perceptions which do not specify any particular content domain. Questions like "How well does your job meet your needs?" or "How well are you able to meet the demands of your job?" would elicit

global fit perceptions. A narrower approach looks at different facets within a domain. For example, a study of interest fit might examine the effects of Realistic interests fit as compared to Social interests fit on an outcome. As previously mentioned, this study examines three content domains simultaneously (cognitive abilities, interests, and personality). It also retains granularity in the data as much as possible by analyzing fit at the facet-level and drawing domain level conclusions from those analyses where appropriate.

Work Satisfaction

Edwards & Shipp (2007) organize the outcomes with which PE fit has been studied into three categories: (1) attitudes, (2) mental and physical health, and (3) performance (task and contextual). This study concentrates exclusively on the first category and specifically on job satisfaction.

Commonly accepted definitions of job satisfaction corroborate its intimate relationship with PE fit. For example, Dawis & Lofquist (1984) define job satisfaction as "a pleasurable affective condition resulting from one's appraisal of the way in which the experienced job situation meets one's needs, values, and expectations." Satisfaction with the work itself is a facet of overall job satisfaction capturing the affective reaction to what a person actually does. Cognitive appraisal of how well the environment meets one's needs (i.e., needs-supplies fit) may be the most proximal antecedent to the affective experience of satisfaction. While supplementary fit may be more distal to satisfaction than NS fit, it can still have a meaningful and distinct influence. Again, Edwards & Shipp (2007) specify three paths through which supplementary fit indirectly affects satisfaction. First, similar people are more likely to develop relationships with and like each other (i.e., homophily; Byrne, 1971). By associating with similar others, supplementary fit can fulfill needs for affiliation and belongingness. Associating with similar

others also increases predictability and decreases ambiguity which fulfills control-related needs like clarity and closure. Additionally, while being too similar to one's peers may thwart desires to be unique, Edwards and Shipp believe that, on balance, supplementary fit has a positive effect on need fulfillment. Second, when people desire similar things from the environment as their colleagues, the environment is more likely to value that and provide it to employees. This can be part of a mutually reinforcing cycle like the one described by Schneider's (1987) ASA model. Lastly, supplementary fit can facilitate better communication between coworkers which can improve workers' abilities to meet environmental demands. In these cases, supplementary fit may distally influence satisfaction via demands-abilities fit.

The individual differences in this study have shown moderate and reliable intercorrelations (Ackerman & Heggestad, 1997), which necessitates analyzing them simultaneously. In addition, given the preceding discussion, there is reason to believe that the various types of fit associated with the facets of each of those domains may be related. For example, a high degree of fit on Openness may be correlated with a high fit on cognitive abilities. Including different fit domains in the same analysis will help to sort through their relative contributions to satisfaction with more precision.

Cognitive Ability and Work Satisfaction

While we know a great deal about the relationship between cognitive ability and performance, little research has examined the relationship with satisfaction or intrinsic career success. Childhood mental ability has shown a moderate positive relationship with future job satisfaction (Judge et al., 1999). Between occupations, the relationship between occupational intelligence and aggregated Occupational Satisfaction is positively correlated ($r = .47$; Ganzach, 1998). However, job complexity plays an important role. Within occupations, intelligence

appears to have a small, negative direct effect on satisfaction but a positive indirect effect via job complexity (Gonzalez-Mulé et al., 2017). People with more ability desire more complex jobs and gravitate to them (Wilk & Sackett, 1996). More complex jobs tend to be more satisfying and to provide more desirable job characteristics (Humphrey et al., 2007). The latter characteristic is likely due to the rarity of the knowledge, skills, and abilities required to perform them. However, when high ability people are underemployed and unable to attain high complexity jobs, they tend to be even more dissatisfied than people with low to moderate ability would be.

This research suggests that matching one's ability level to the job is important to meet individual expectations and produce satisfaction. However, very little research has examined the relationship between DA fit and satisfaction, and this may be due to the assumption that any effect of DA fit on satisfaction works through NS fit by meeting needs more effectively. What little research has been done has measured perceived rather than objective fit. For example, Cable & DeRue (2002) found that DA fit correlated moderately with job satisfaction ($r = .33$). However, as theory would predict, this effect was not significant in a regression that included perceived NS fit and person-organization fit. Rehfuss et al. (2012) replicated these findings in a separate sample. Other studies have found larger zero-order correlations between perceived DA fit and satisfaction ranging from $r = .43$ (Michael, 2009) to $r = .58$ (Bogler & Nir, 2015; Ishola, 2013). Together, these studies demonstrate the significant discrepancies between perceived and objective fit. First, perceived NS fit is conceptually and operationally similar to Work Satisfaction, so these are probably overestimates of the relationship. Second, Cable & DeRue (2002) mention that DA fit may have been affected by range restriction, as people tend to skew their self-rated abilities upward. Additional range restriction could exist due to individual self-selection into occupations. The present study operationalizes objective fit by assessing abilities

rather than asking participants to self-report them, which sidesteps the first form of range restriction but not the second. While self-reported variables are more common in PE fit research, the level of ability in the environment and the fit between an individual's ability and the environment is likely to explain incremental variance in Work Satisfaction beyond interests and personality.

Personality and Work Satisfaction

A previously cited meta-analytic regression found that job satisfaction was reliably related to Extraversion ($\rho = .21$), Neuroticism ($\beta = -.20$), and Conscientiousness ($\rho = .20$; Judge et al., 2002). In total, the FFM factors showed a multiple R of .41. Because Extraversion and Neuroticism are strongly linked with positive and negative affectivity, their role in satisfaction has received the most attention. A longitudinal study found that when personality was measured during childhood, the significant bivariate relationships of E and N with intrinsic career success disappeared, and Conscientiousness was the only significant predictor ($\beta = .34$; Judge et al., 1999). It is possible that early Conscientiousness predicts intrinsic career success through greater achievement, job complexity, and income. Agreeableness may have a small effect on job satisfaction while Openness has essentially no effect (Judge & Kammeyer-Mueller, 2007). Career satisfaction is related to Neuroticism (-.36) and Extraversion (.27), but relationships between the FFM factors and extrinsic career success like salary and promotions are small (Ng et al., 2005). While Extraversion and Neuroticism are the most consistent predictors of job satisfaction, Conscientiousness was also a significant predictor.

Almost no research has examined how the fit between an employee's personality and the mean personality of the occupation can affect job satisfaction. Törnroos et al. (2019) found significant person-environment interactions for both Neuroticism and Openness. The negative

association between individual Neuroticism and job satisfaction was greater when occupational Neuroticism was low. This suggests that people higher in Neuroticism than their average colleague will be even less satisfied than if they were in a more congruent environment. In addition, the slope for Openness was negative when occupational Openness was low. In the same way that high ability employees tend to be dissatisfied with low complexity jobs, it appears that highly open employees are more dissatisfied when the environment cannot meet their level of Openness. As Nye, Prasad, et al. (2018) found for interests, this study found that occupational personality levels explained much more variance in job satisfaction than individual levels.

Vocational Interests and Work Satisfaction

While the previous sections focused mainly on the direct effects of ability and personality on satisfaction, most all research on vocational interest has focused on congruence as a predictor of satisfaction. Several meta-analyses have investigated the much-theorized relationship between interest congruence and job satisfaction. Assouline & Meir (1987) found a non-significant overall correlation of .21 between congruence and job satisfaction. However, separating that effect by level of congruence showed meaningful variation. While general occupational congruence had a non-significant effect on satisfaction, the effect of congruence of one's narrower specialty in the occupation was relatively strong and significant ($r = .42$). This effect may be skewed by one study with a particularly high effect, but the remaining effect sizes ranged from .26 to .46. In addition, congruence with others in the environment (i.e., supplementary fit) showed a significant mean correlation with satisfaction of .29. They also found a great deal of variation between operationalizations of congruence as did Camp & Chartrand (1992). Overall, their results suggest that maintaining granularity in occupational categorizations is important for

detecting congruence effects, supplementary fit may have a stronger effect than theory would suggest, and congruence operationalization matters.

Tranberg et al. (1993) also found a non-significant effect of interest congruence on satisfaction. They found that the effect varied by RIASEC type (e.g., people with Social as their primary interest benefited the most from congruence while Realistic people benefited the least). While the results cast even more doubt on an overall effect of congruence on satisfaction, the differences between RIASEC types is an important consideration for which the direct effects of polynomial regression can account.

In a dissertation, Morris (2003) found a similar effect size ($\rho = .24$) that was statistically significant. However, removal of a large military study ($n = 18{,}000$) not included in the previous meta-analyses expanded the confidence interval to include zero. Similar to the previous study, more established and empirically validated interest measures tended to produce smaller effect sizes.

Tsabari et al. (2005) again found a non-significant overall correlation. When the environment was operationalized at the occupation-level, the effect was significant, but the supplementary fit result found in Assouline & Meir (1987) did not replicate. The pattern of effect sizes by RIASEC types also did not replicate suggesting that more research is needed to determine whether some types are really more or less sensitive to fit.

Lastly, in a thesis, Earl (2014) found that "matched scale scores" (i.e., direct correlations between interest scores and satisfaction) produced higher effects sizes than congruence indices ($\rho = .20$ and $\rho = .08$ respectively). This provides further evidence that the direct effects of interests on satisfaction should not be ignored. In addition, polynomial regression has also been

shown to improve the validity between interest congruence and job satisfaction (Nye, Prasad, et al., 2018).

Hypotheses

While there are reliable correlations between individual difference domains, they are distinct enough to suggest that each one should explain unique variance in Work Satisfaction. There will almost certainly be variation in *how* each domain predicts satisfaction. For example, prior research suggests that the ability level of the environment will likely explain more variance than that of the individual, squared, and interaction terms in polynomial regression (Dalal et al., 2013; Nye, Prasad, et al., 2018). Conversely, congruence may be relatively more important for interests. Broadly, each of the three domains should explain unique variance in Work Satisfaction and support the adoption of an integrated perspective in person-environment fit research. Each dimension is represented with a polynomial regression model, so the domains being compared in this case are broadly construed to include not just the main effects of person and environment but the fit between them as well. This is summarized in the following three hypotheses:

H2a: The ability domain will explain incremental variance in Work Satisfaction beyond personality and interests.

H2b: The personality domain will explain incremental variance in Work Satisfaction beyond ability and interests.

H2c: The interest domain will explain incremental variance in Work Satisfaction beyond ability and personality.

To build on these analyses, this study uses response surface methodology (Edwards & Parry, 1993) to compare the form of fit between individual difference domains more explicitly.

Analyzing the shapes of three-dimensional surface plots, both visually and mathematically, allows a more nuanced interpretation of fit relationships. Prior research suggests that some individual difference domains may be more important for satisfaction than others. Of the three individual difference domains in this study, most congruence studies using polynomial regression have focused on vocational interests (Nye, Prasad, et al., 2018; Wiegand, 2018). However, the research summarized above suggests that personality and ability fit may also add incremental validity to the prediction of job satisfaction. While we tend to like people who are similar to ourselves (Byrne, 1971), we also want to feel different and unique from others (Hornsey & Jetten, 2004). It is possible that a variety of personalities in the workplace might contribute to the richness of a workplace culture and, therefore, support satisfaction. While the ability domain in general should have a strong relationship with satisfaction (mostly through the ability of the environment), ability congruence should be less influential. Therefore, it is hypothesized that interest fit should explain the most variance in Work Satisfaction, and personality and ability fit will follow in that order.

H3a: The effect of interest fit on Work Satisfaction will be greater than the effects of either ability fit or personality fit.

H3b: The effect of personality fit on Work Satisfaction will be greater than the effect of ability fit.

Multidimensional scaling as described above will yield higher-order dimensions that will summarize all the individual differences at a more general level of abstraction. Intuition might suggest that these summary measures will have lower predictive validity since a summary sacrifices information. However, research on the bandwidth-fidelity dilemma suggests that matching predictors and criteria at the same level of generality tends to produce the highest

criterion validity (Ones & Viswesvaran, 1996). Thus, while most of the focus of this study is on Work Satisfaction or satisfaction with the work itself, broader MDS dimensions should match better with general job satisfaction (i.e., broad reports of an individual's satisfaction with all aspects of the job).

H4: Using higher-order dimensions identified using multidimensional scaling as predictors will explain more variance in overall Job Satisfaction than in the facet of Work Satisfaction.

METHOD

Participants

Data for this study comes from Project TALENT (PT; Wise et al., 1979) a large-scale study of high school students with follow-ups 1, 5, and 11 years after high school. This dataset is well-suited to the current study because it is a large, nationally representative sample that measures all three individual differences. None of the more recent studies of comparable scope measure abilities, interests, and personality.

The first measurement in Project TALENT took place in 1960 and sampled students from American secondary schools. To ensure representativeness, the sample of schools was stratified by type of school (public, Catholic, and private/non-Catholic) and by geography. Public schools were further stratified by size and retention. Specifically, participants came from 987 high schools and 238 junior high schools in which all students from grades 9 through 12 were included (i.e., 9th graders were 14.8 years old on average while 12th graders were 17.7 years old). While ages varied at baseline, follow-up studies were staggered such that all participants were expected to be roughly the same age at each follow-up (i.e., roughly 19 at the year 1 follow-up, 23 at year 5, and 29 at year 11).

The dataset includes a Response Credibility Index (Wise et al., 1979) based on attention checks intended to detect careless responding (e.g., “how many days are in a week?”). In total, 30,355 participants were removed for low credibility responses lowering the full sample size to 346,661.

Sex of the participants is split almost exactly in half with 178,970 being female. Race, for a large proportion of respondents, is unknown, conflicting, or missing. Table 1 shows the racial makeup of the sample and compares proportions to those in the country overall at the time

(United States Census Bureau, 1960). Note that Black participants are underrepresented in the sample while White participants are overrepresented. Students are distributed more or less equally between the four grades or cohorts in high school (9th grade = 26.43%, 10th grade = 26.26%, 11th grade = 25.02%, 12th grade = 22.29%).

Table 1

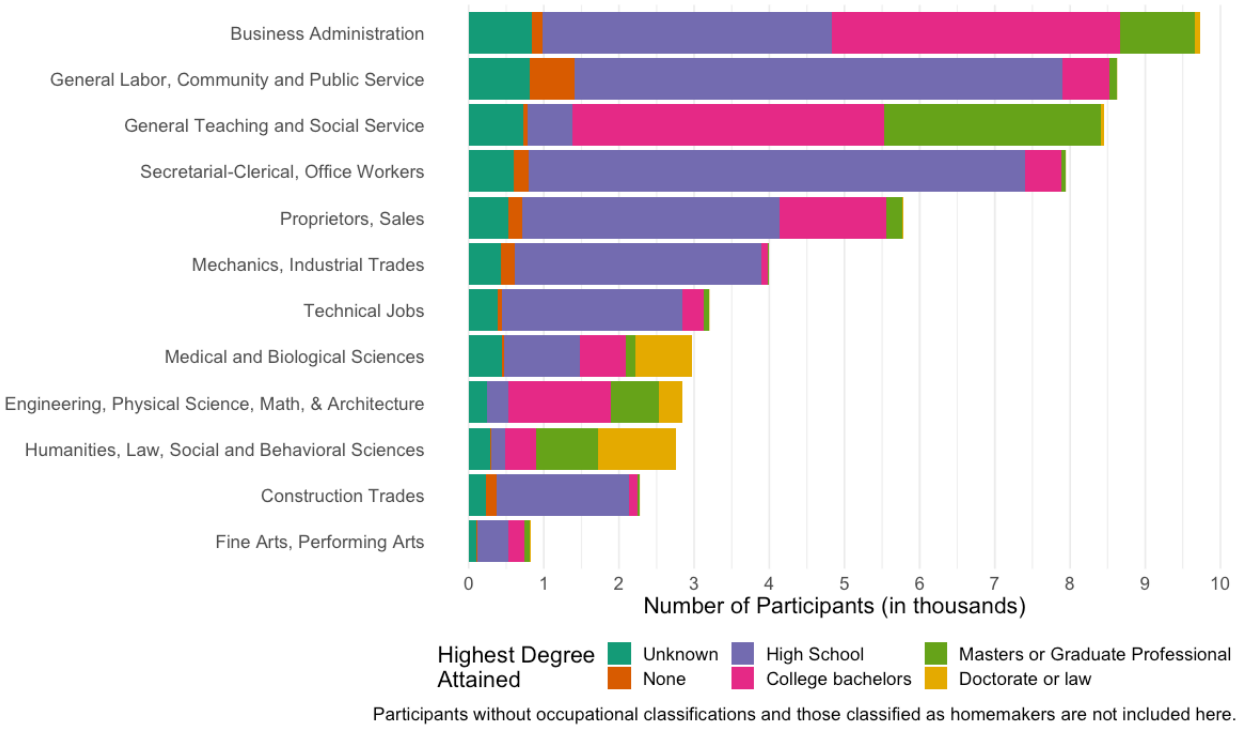
Racial Composition of Project TALENT Sample

Race	n	%	% w/o Unknown	% Census
Unknown or conflicting	193,363	55.78%		
White	141,233	40.74%	95.51%	88.57%
Black	5,126	1.48%	3.47%	10.52%
Did not answer	4,114	1.19%		
(Missing)	1,311	.38%		
Asian	967	.28%	.65%	.49%
Hispanic	324	.09%	.22%	
Native American	223	.06%	.15%	.29%

For the analyses predicting future satisfaction, this study uses data from the 11-year follow-up which includes 89,784 of the remaining participants. Because meta-analytic evidence suggests little difference in job satisfaction between full- and part-time employees (Thorsteinson, 2003), this study includes all employees who report a valid occupation. Figure 1 shows the distribution of participants across Project TALENT's occupational categories along with their highest degree achieved. This figure demonstrates the breadth of jobs and education levels that are represented in the sample.

Figure 1

Number of Participants by Occupational Category and Highest Degree Attained



Measures

Cognitive abilities, personality, and interests were measured in 1960 while occupational information and satisfaction data were collected at follow-up studies.

Cognitive Abilities

Project TALENT included a variety of knowledge and ability tests in the 1960 baseline assessment. In this study, a list of PT tests which count as ability tests was first assembled and subjected to parallel analysis to reveal that a 5-factor EFA solution was best. However, some scales constructed from this 5-factor EFA had inadequate Cronbach α reliabilities: Memory = .46, Math = .44, Perceptual Speed = .66, Verbal = .73, Spatial = .77.

Given the inadequacy of an EFA solution, Wai et al. (2009) created Mathematics, Verbal, and Spatial ability composites from the PT data. The present study built on that work to create

composites for the proposed analyses (see Table 2). To prevent individual scales from being overemphasized, each score was divided by the scale maximum (i.e., converted to proportion of total possible correct), and then unit weights were used to construct each composite as done by Su (2012) and Damian et al. (2015). Finally, these composites were each standardized. The α reliabilities were Mathematics = .87, Verbal = .85, and Spatial = .80.

Table 2

Project TALENT Ability Tests Used in this Study

Composite	Scale	# of items	Description
Math	Mathematics Information	23	Knowledge of math definitions and notation.
	Arithmetic Reasoning	16	Reasoning ability needed to solve basic arithmetic items.
	Introductory Mathematics	24	All forms of math knowledge taught through the 9th grade.
	Advanced Mathematics	14	Algebra, plane and solid geometry, probability, logic, logarithms, and basic calculus.
Verbal	Vocabulary	30	General knowledge of words.
	English Composite	113	Capitalization, punctuation, spelling, usage, and effective expression.
	Reading Comprehension	48	Comprehension of written text covering a broad range of topics.
Spatial	3D Spatial Visualization	16	Visualize two-dimensional figures after they had been folded into three-dimensional figures.
	2D Spatial Visualization	24	Visualize two-dimensional figures when they were rotated or flipped in a plane.
	Mechanical Reasoning	20	Deduce relationships between gears, pulleys, and springs as well as knowledge of the effects of basic physical forces, such as gravity.
	Abstract Reasoning	15	Nonverbal measure of finding logical relationships in sophisticated figure patterns.

Personality

To assess personality, participants were asked to indicate how well various sentences described them (descriptions of each dimension listed in Table 3). Specifically, the instructions

were “Regarding the things I do and the way I do them, this statement describes me A) extremely well B) quite well C) fairly well D) slightly E) not very well”. Project TALENT only includes item-level personality data for 4% of the total sample. Because limiting analyses to this small subsample would decrease power, personality analyses were conducted using the scale scores for the factors shown in Table 3.

To better approximate the FFM factors, Pozzebon et al. (2013) created a crosswalk between PT personality scales and the FFM. The current study divided each score by its scale maximum, created unit-weighted FFM composites according to the Pozzebon et al. (2013) mappings in Table 3, and standardized those composites.

Table 3

Project TALENT Personality Dimensions

FFM Factor	PT Factor	# of Items	α	Description
Extraversion	Sociability	12	.83	Tendency to enjoy being with people as well as to be optimistic
	Vigor	7	.86	Physical activity level of a person
	Leadership	5	.79	Activities such as taking charge and seeking out responsibilities
Agreeableness	Social Sensitivity	9	.85	Propensity to put oneself in another's place
Conscientiousness	Mature Personality	24	.93	Ability to get work done efficiently, to work on a project to completion, and to accept assigned responsibility
	Impulsiveness	9	.72	Tendency to make quick decisions without full consideration of the outcomes
	Tidiness	11	.86	Desire for order and neatness in one's environment
Emotional Stability	Self-Confidence	12	.78	One's feelings of social acceptability and the willingness to act and think independently
	Calmness	9	.87	Ability to react to emotional situations in an appropriate manner without displaying extreme emotions
Openness to Experience	Culture	10	.81	Tendency to recognize the value of aesthetic things, and to display refinement and good taste

Note: Scale descriptions and reliabilities are from Pozzebon et al. (2013)

Interests

Interests were assessed with 205 items of two types. The first group listed 122 different occupations and asked participants to rate how much they would like the work that each entails. The remainder listed activities, and again participants rated how much they would like to do that activity. Participants responded on a 5-point scale from “A) I would like this very much” to “E) I would dislike this very much”. The original research staff categorized the 205 items into 17 factors a priori. Using a top-down factor analysis, Su (2012) found interest factors similar to the

RIASEC: Things, Science, Artistic, People, Leadership, and Business. Alternatively, Wiegand (2018) formed RIASEC factors through content analysis and categorized relevant items into one of the six Holland groupings with 9 items per factor. Due to superior concordance with the well-researched RIASEC dimensions and the reliability evidence, this study created interest scores according to the procedure outlined by Wiegand (see Table 4 for those mappings). Reliabilities for interest composites were as follows: Realistic = .89, Investigative = .84, Artistic = .85, Social = .82, Enterprising = .84, Conventional = .81.

Table 4

Project TALENT Interest Items Mapped to RIASEC Dimensions

Realistic	Investigative	Artistic
Toolmaker	Surgeon	Musician
Automobile Mechanic	Chemist	Reporter
Electrician	Astronomer	Sculptor
Electronics technician	Research scientist	Author of a novel
Bricklayer	Doctor	Interpreter
House Painter	Biologist	Writer
Machinist	Laboratory technician	Musical composer
Carpenter	Physics	Poet
Operate a crane or derrick	Studying	Artist
Social	**Enterprising**	**Conventional**
Social worker	Personnel administrator	Bookkeeper
Elementary school teacher	Credit manager	Bank teller
Guidance counselor	President of a large company	Office clerk
College professor	Real estate agent	Certified Public Accountant
High school teacher	Office manager	Typist
Religious worker	Banker	Accountant or auditor
School principal	Salesman	Type setter
Sociology	Manage a large store	Make out income tax returns
Teach children	Sell merchandise to stores	Keep accounts

Note: Mappings are from Wiegand (2018)

Environment

Person-level scores for all the preceding individual difference measures were used to create environment scores. For each person, the environment score was computed as the mean trait level of everyone who shared the same occupation. This operationalization of the environment captures supplementary fit or how similar people are to those who share their occupational group.

Consistent with previous research (Nye, Prasad, et al., 2018), occupations with fewer than 10 members were excluded from fit analyses since the reliability of environment ratings depends on the number of individuals considered. To minimize the number of discarded participants, this study used Project TALENT's 3-digit job codes which lump more people into slightly fewer categories than the 4-digit codes. Of the 258 actual occupations reported in this remaining sample, 241 had 10 or more people in them leaving a final sample size of 58,571 with complete data for predictive analyses. To aid interpretation and mitigate multicollinearity, all person scores were standardized before creating squared and interaction terms.

External ratings of the environment (e.g., from O*NET) were not used in this study for several reasons. First, there is roughly a 50-year gap between when PT participants reported on their jobs and modern O*NET job ratings. While there are expert rated job characteristics produced closer to the 1971 data collection in this study (e.g., the DOT), they do not have ratings of all three individual difference domains nor do they have data at the level of granularity that this study requires (e.g., they may report interests as a three-letter code rather than as scale scores). Second, based on prior studies that have matched occupations based on content (Reeve & Heggestad, 2004; Wiegand, 2018), less than 70% of the occupations in the PT dataset can be crosswalked to the O*NET. Third, the occupations that do have matches lose fidelity by first

requiring a match to DOT occupations and then to the O*NET. Lastly, prior PE fit studies that match characteristics to O*NET ratings have found significantly lower effect sizes compared to the already commensurate supplementary fit operationalizations (e.g., Nye, Prasad, et al., 2018).

Satisfaction

While there were three follow-ups after high school, the job satisfaction measures were not consistent across follow-ups or across cohorts within follow-ups. Therefore, only the 11-year follow-up measurement can be used in this study.

The primary focus of this study is satisfaction with the work itself or Work Satisfaction. While satisfaction with other job characteristics like pay and coworkers are important, they are more job-specific than the work itself which will tend to be more stable between jobs within an occupation. In this way, it is a more useful benchmark for the quality of one's occupational choice. One general item in Project TALENT taps this domain by asking participants, "Do you enjoy the kind of work you have done on this job?". This broad item was combined with three more specific ones about how interesting, challenging, and meaningful the job is.

An overall job satisfaction measure will also be required to test the hypothesis that higher-order dimensions from MDS can predict the broader outcome of overall job satisfaction (as compared to the facet of Work Satisfaction). A broad item tapping general satisfaction in Project TALENT asks, "Considering all aspects, how do you feel about your job?". To build a more reliable, multi-item measure that captures a greater proportion of the construct space, other more specific job satisfaction items were also included if they were: (1) administered to most, if not all, high school cohorts, and (2) construct valid. Items with inadequate construct validity include "My job has short hours" and "My job has long vacations". Table 5 lists all items along with their rating anchors.

Because the items used to construct both work and job satisfaction have slightly different scale ranges, all satisfaction items were divided by their respective scale maxima before being averaged to compute composite scores and then standardized. Cronbach's alphas for work and job satisfaction were .88 and .87 respectively.

Table 5

Items in Overall Job Satisfaction Measure and Work Satisfaction Subset

Item Content	Rating Anchors
*Do you enjoy the kind of work you have done on this job?	1 - No, I hate the work 2 - No, I dislike it very much most of the time 3 - No, I rather dislike it 4 - I have no feelings about it 5 - Yes, I rather like it 6 - Yes, I like it very much most of the time 7 - Yes, I enjoy it very much
*My job has work that is important or worthwhile. *My job has work that is challenging. *My job has interesting work. My job has a good income to start. My job will have a good income within a few years. My job has job security and permanence. My job has opportunity for promotion. My job has work that I feel I do well. My job has friendly likeable coworkers. My job has pleasant surroundings. My job gives status. My job is a job that provides real power.	1 - This Job is terrible in this respect 2 - This Job is very poor in that respect 3 - This Job is rather poor in this respect 4 - This Job is adequate in this respect 5 - This Job is very good in this respect 6 - This job is excellent in that respect
Considering all aspects, how do you feel about your job?	1 - Very dissatisfied with it 2 - Rather dissatisfied with it 3 - Neither satisfied nor dissatisfied 4 - Fairly satisfied with it 5 - Very satisfied with it

* items are part of the Work Satisfaction subset which will be the main focus of this study. Those along with all remaining items were used to construct an overall Job Satisfaction score.

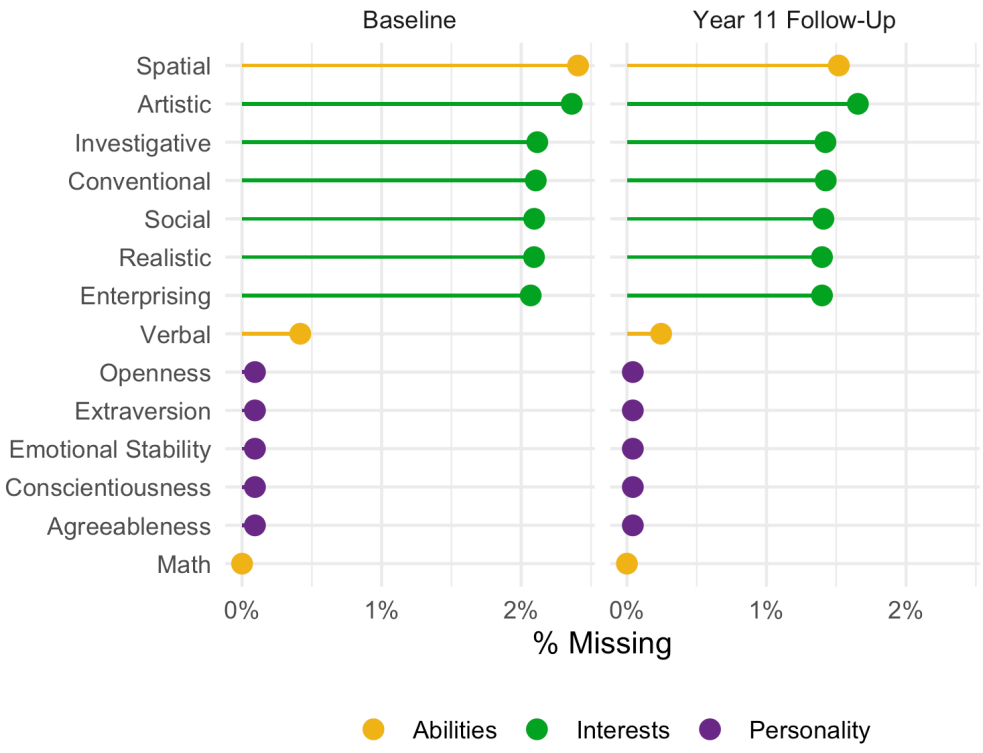
Data Preparation

Missing Data

Construct-level missingness refers to the percentage of respondents who do not have at least one valid answer to any of the items included in a construct or scale. Figure 2 shows the construct-level missingness for each individual difference in the study, both at the 1960 baseline measurement and for participants with valid responses at the 11-year follow-up. Newman (2014) suggests that when construct-level missingness is less than 10%, techniques such as listwise deletion produce similar results to multiple imputation or full-information maximum likelihood. Therefore, this study will use simpler methods like pairwise deletion in multidimensional scaling and listwise deletion in polynomial regression.

Figure 2

Construct-Level Missingness



Outlier Identification

One way to mitigate overfitting is to identify and potentially remove outlying observations. For the multidimensional scaling analyses which have no outcome variable, observations with leverage values (i.e., a measure of how unusual an observation is relative to the mean values across all predictors) exceeding the cutoff for large samples suggested by Bollen & Jackman (1990) were identified as outliers and removed (239 cases in total).

For the polynomial regression analyses, this study followed the procedure described in Edwards et al. (2006). That is, in order to be considered an outlier, a case needed to exceed the cutoffs from Bollen & Jackman (1990) on all of the following metrics: (1) leverage, (2) studentized residuals, and (3) Cook's distance. According to these guidelines, Cook's distance was the most conservative, as it identified no cases as outliers. Therefore, no observations were removed for polynomial regression analyses.

Analyses

Multidimensional Scaling

As described above, multidimensional scaling (MDS) is particularly useful for mapping the relationships between constructs. It plots variables based on their relative similarities such that distance in a plot decreases monotonically with greater correlation or similarity. MDS is often preferable to factor analysis when variables show a circumplex relationship as the RIASEC interests do. Mount et al. (2005) used MDS to integrate personality and vocational interests with the goal of understanding motivation more comprehensively. This understanding can lead to theoretical development as it has in the identification of higher-order factors of personality (i.e., factors α and β). For example, integrity (which relates to Conscientiousness, Agreeableness, and Emotional Stability; Connelly et al., 2018), is a valuable predictor of job performance and

overlaps a great deal with factor α or Stability. In addition to producing a more comprehensive and integrative map of the individual difference space, the dimensions extracted with MDS can also be used to build more parsimonious predictors. This is particularly relevant for integration when the number of dimensions combined with polynomial regression leads to a very high number of parameter estimates.

The first step in multidimensional scaling is to determine the appropriate number of dimensions for the model. Following the example of Mount et al. (2005), this will be done both quantitatively and qualitatively. That is, better models should fit the data better (i.e., through lower stress values) without capitalizing on chance (as when the ratio of constructs to MDS dimensions is significantly less than 4:1), and they should also have dimensions that are interpretable and coherent. For example, if Conventional interests lie at the high side of a dimension and Artistic interests lie at the other side, it would support the existence of a Conformity dimension in the data. Additionally, visualizations plotting each dimension relative to every other will be able to identify broader integrative patterns.

Multilevel Polynomial Regression

Tinsley (2000) lists several key limitations of the interest congruence research that may have attenuated effect size estimates. First, because most studies only include a small range of employee types and occupations, both sides of the PE fit operationalization have restricted ranges. This reduces the variation in fit scores which attenuates validities. Second, many studies do not measure person, environment, and outcome variables on the same dimensions or at the same level of abstraction. For example, when a person variable represents the desired level of pay while the environment variable to which it is compared represents the importance of pay, this would be a dimension mismatch. Tinsley offers an example of a mismatch of abstraction

when a measure of pay fit is used to predict general satisfaction rather than just pay satisfaction. Person and environment variables can also be mismatched on abstraction (e.g., comparing a person's desired level of base pay to the environment's level of total compensation including benefits). The TWA measurement paradigm (Dawis, 1991) is internally consistent such that all three variables can be measured on similar scales. Mismatch between content domains or bandwidth in these measures can attenuate correlations. Third, most of the studies in interest-congruence meta-analyses (e.g., Assouline & Meir, 1987; Tranberg et al., 1993) relied on congruence indices which combine separate P and E values into a single fit score. Tinsley (2000) points out that:

> …indices based on the algebraic difference discard information about the absolute level of the person and job measures. Absolute and squared difference indices also discard directional information (i.e., whether supply exceeds demand or vice versa). All fit indices discard information about the relative contribution of each factor to the index. (pp. 152-153)

Congruence indices are not as reliable as the scores used to make them (Edwards, 1994). Tinsley also points out that PE fit studies often do not compare the predictive validity of the environment alone to the less parsimonious PE fit model. For example, an environment with a generally high level of supplies may be more likely to satisfy all employees, regardless of unique individual preferences. This concern is based on empirical research showing that environment scores are significantly more important for predicting job satisfaction than are person scores (Nye, Prasad, et al., 2018) and that environment scores may predict about as well as PE fit models (Edwards, 1991). Lastly, he asserts that Holland's (1973) hexagonal RIASEC model is

an inadequate base for PE fit studies due to the incommensurate environment measures and the multifaceted and ambiguous nature of the RIASEC types.

A common and significant limitation of interest congruence meta-analyses in particular is that they focus almost exclusively on studies that use congruence indices. Edwards (1993; 1994) has documented a variety of advantages of polynomial regression over more traditional fit operationalizations like difference scores and profile correlations. Most notably, polynomial regression does not impose unintentional constraints on the regression model the way other indices do. For example, in the typical 5-term polynomial regression equation ($Z = b_0 + b_1P + b_2E + b_3P^2 + b_4PE + b_5E^2$ where P is the person and E is the environment), all parameters in the model (b_0 through b_5) are estimated separately rather than constrained to be equal or opposite. Combining all the individual differences in this study yields a complex equation, but the large sample size accommodates it.

Hypotheses 2a-2c in this study posit that each of the three domains will explain unique variance in Work Satisfaction. These hypotheses were tested using hierarchical polynomial regression models that include all individual difference dimensions within various domains. For example, to test whether or not interests explain incremental, out-of-sample variance, the full polynomial model is compared to one that only includes constructs from the ability and personality domains.

Because the environment scores in this study are constructed from the person scores, the environment scores are not independent across participants within the same group. This violates an assumption of linear regression, so this study uses a multilevel model to account for the nested data structure: $Z_{ij} = b_0 + b_1P_{ij} + b_2E_j + b_3P_{ij}^2 + b_4P_{ij}E_j + b_5E_j^2 + u_{0j}$ where subscript i represents a particular participant, subscript j represents a particular occupation, and u_{0j} is an

intercept which is allowed to vary between occupations. Bleidorn et al. (2016) used a similar method when they operationalized the personality of a city by the average level of participants in that city and then used multilevel polynomial regression in which intercepts were allowed to vary by city. This method also allows examination of whether and to what extent psychological variables predict Work Satisfaction above and beyond a baseline multilevel model which only includes a random intercept. While it is best practice to include random slopes for lower-level terms when the model includes cross-level interactions (Heisig & Schaeffer, 2019), the inclusion of random slopes in this study did not add incremental predictive validity and sometimes actually hindered prediction. Thus, while it is possible that the shape of response surfaces could vary across occupations, allowing the model that degree of flexibility appeared to overfit the data compared to a random intercept model in which only the elevation of surfaces could vary. Combined with the significant cost of random slopes in terms of model convergence, model complexity, and computing power, the random intercept model used by Bleidorn et al. (2016) was retained.

Tinsley (2000) points out that the flexibility of polynomial regression risks fitting to sample-specific noise, hindering generalizability, and inflating estimates of predictive capabilities. While the sample in this study is occupationally diverse, relatively flexible models mean that overfitting to the data is still a concern. For this reason, k-fold cross-validation with 10 folds was used to determine the stability of model performance. That is, the dataset was randomly split into 10 samples, stratified by occupation. Then, for each sample, the remaining 9/10 of the data were used to train a model and predictive validity was tested in the hold-out sample. This same k-fold cross validation procedure was performed on MDS predictors to test

hypothesis 3 (i.e., that MDS dimensions will predict Job Satisfaction better than the facet of Work Satisfaction).

Response Surface Methodology

A congruence hypothesis, as posed in this study, stipulates that an outcome variable will be higher (or lower) when two predictor variables are roughly equivalent (Nestler et al., 2019). Unfortunately, congruence cannot be encapsulated into a single value and simply correlated with an outcome (Edwards, 1993). Instead, response surface methodology (RSA; Edwards & Parry, 1993) is an appropriate analytical strategy which will allow a more nuanced examination of how fit contributes to Work Satisfaction. In addition to visual inspection of a three-dimensional plot (i.e., person, environment, and outcome), RSA provides a way to run significance tests on the slopes and curvatures of the surface. This technique will help to assess the validity of hypotheses 3a and 3b regarding the relative importance of fit across individual difference domains.

In this study, the hypothesized positive effects of fit on satisfaction should yield a surface that is relatively high along the line of congruence (LOC; $P = E$) and relatively lower as misfit increases along the line of incongruence (LOIC; $P = -E$). Specifically, there will be evidence of fit if the response surface shows something like a saddle or inverted-U shape in which satisfaction is maximized along the line of fit and then decreases on either side of this line.

Nestler et al. (2019) describe three criteria which should be met to support a congruence hypothesis. Before describing them, it is worth noting that their congruence criteria are relatively strict compared to how prior researchers have conceptualized congruence relationships (e.g., Edwards, 2002), and it is possible to have a different type of congruence relationship which would not satisfy all or any of the criteria in Nestler et al. (2019). The first criterion is that the LOC should be flat: there should be no slope or curvature along the line when $P = E$. Parameters

to test this are constructed with regression coefficients such that the slope along the LOC is $a_1 = b_P + b_E$ and the curvature along the LOC is $a_2 = b_{P^2} + b_{PE} + b_{E^2}$. This condition is met when neither of these is significantly different from zero. If the surface fails these criteria, it cannot be considered a *strict* congruence relationship according to Nestler et al. (2019), but it can still be considered a *broad* congruence if it satisfies the remaining criteria. This study will only evaluate the presence of broad congruence such that a surface which has slope or curvature along the line of fit can still be considered evidence in favor of a congruence hypothesis.

The second criterion, as described above, is that there should be an inverted-U shaped curve along the LOIC and that this curve should peak at the origin (i.e., when $P = E = 0$). Just as a_1 and a_2 represent the slope and curvature along the LOC respectively, a_3 and a_4 represent the slope and curvature along the LOIC. A value for a_3 $(b_P - b_E)$ that is not significantly different from zero means that the slope of that curve is roughly zero when both person and environment equal zero. A negative and statistically significant a_4 parameter defined as $b_{P^2} - b_{PE} + b_{E^2}$ is evidence of the inverted-U shape. Because this metric describes the line of misfit, substituting E for $-P$ in the typical polynomial regression equation shows how a_4 is derived: $Z = b_0 + (b_P - b_E)P + (b_{P^2} - b_{PE} + b_{E^2})P^2$.

Lastly, the LOC should line up with the first principal axis which is defined as the line with the least amount of downward curvature (or the most amount of upward curvature). This is equivalent to saying that the squared-terms for person and environment should be equal or that $a_5 = b_{P^2} - b_{E^2}$ should not be significantly different from zero.

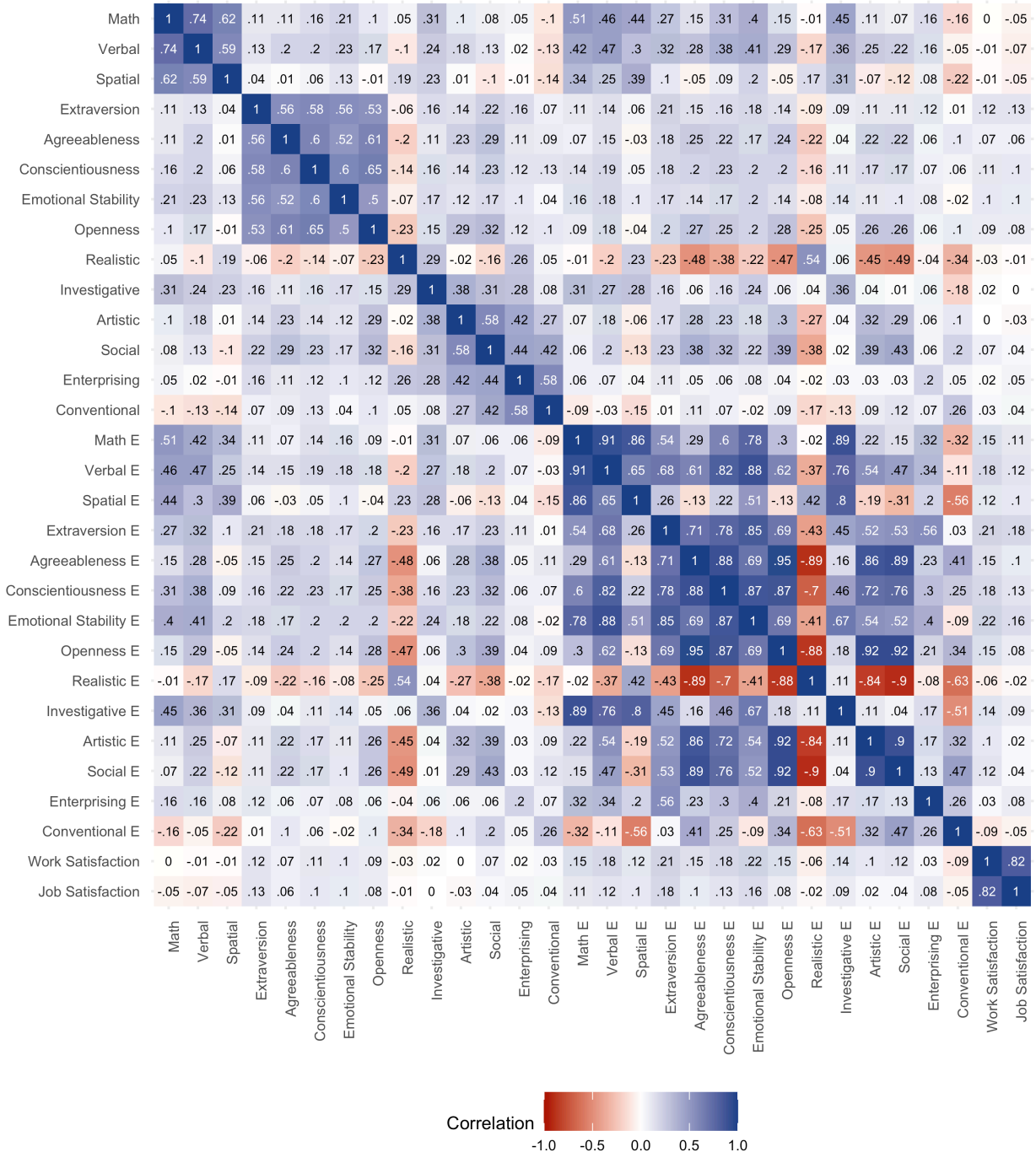
Note that this method of assessing fit through response surface analysis assumes that all other variables are held constant. However, Figure 3 shows some moderate-to-high intra-domain and inter-domain correlations which make this assumption untenable in this study. Nevertheless,

assessing the extent to which a surface conforms to this conception of ideal or exact fit is valuable for interpreting the nature of fit relationships.

Most fit studies using RSA build surfaces one isolated equation at a time (e.g., one 5-variable polynomial regression equation assessing fit on Realistic interests alone). While this study does analyze those plots, it also examines surfaces produced from the combined model. Coefficients pertaining to a particular individual difference were pulled from the large model to construct a surface in the same way, but the plot must be interpreted with the assumption that all other variables are held constant. While all other analyses in this studied used standardized environment scores, response surface analysis was done with unstandardized environment scores in order to maintain numeric congruence along the line of congruence for each surface.

Figure 3

Correlations Among Person and Environment Variables



All correlations greater than .01 in absolute value are significant to the $p < .001$ level.

Figure 3 shows all intercorrelations between all individual differences (i.e., both person and environment) as well as the Work and Job satisfaction measures.

H1a - Distances Between Domains

A matrix of Euclidean distances between all individual difference constructs was created to test whether the mean Euclidean distances between individual difference domains are significantly different. The mean distance between Ability and Personality was 778.5, the mean distance between Ability and Interests was 806.4, and the mean distance between Personality and Interests was 784.1. An ANOVA confirms that there is no significant difference between these means: $F(2,60) = 1.37$, $MSE = 2{,}845.40$, $p = .262$. Therefore, H1a which posited that personality and interests, as non-cognitive traits, would be closer to one another than to abilities is not supported.

H1b - Multidimensional Scaling

Stress values were computed to determine the appropriate number of dimensions to extract in a multidimensional scaling model. Stress compares the actual Euclidean distances between constructs with the model's predicted distances in multidimensional space. It is a "badness-of-fit" measure such that higher stress values indicate less correspondence between the model and the data. Extracting more dimensions reduces stress by creating a more flexible model, but extracting too many dimensions risks overfitting the data. Kruskal & Wish (1978) suggest that achieving a stress value of .1 or lower is a reasonable cutoff to strike this balance. The left side of Figure 4 shows stress values across different numbers of MDS dimensions (k) along with the proportions of variance (R^2) in Euclidean distances accounted for by each model. The stress 1 level at $k = 4$ meets the stress $< .1$ criterion. While $k = 3$ technically meets this criterion as well, $k = 4$ shows a more distinct elbow in stress values. Extracting the fourth

dimension is also what allows examination of the RIASEC circumplex as required to test hypothesis 1b. That is, dimensions 1 & 2 separate between individual difference domains, while dimensions 3 & 4 map something resembling the RIASEC interest circumplex with personality and ability constructs integrated. While using five or more dimensions would produce lower stress levels, Kruskal & Wish (1978) say that a ratio of variables to MDS dimensions that is higher than 4:1 risks capitalizing on chance. Using more than four dimensions would violate this rule. Additionally, dimensions beyond four were not easily interpretable. The right side of Figure 4 indicates that a linear relationship between Euclidean and MDS distances represents the data well in a four-dimension model.

Figure 4

Stress and Shepard Plots for MDS Analyses

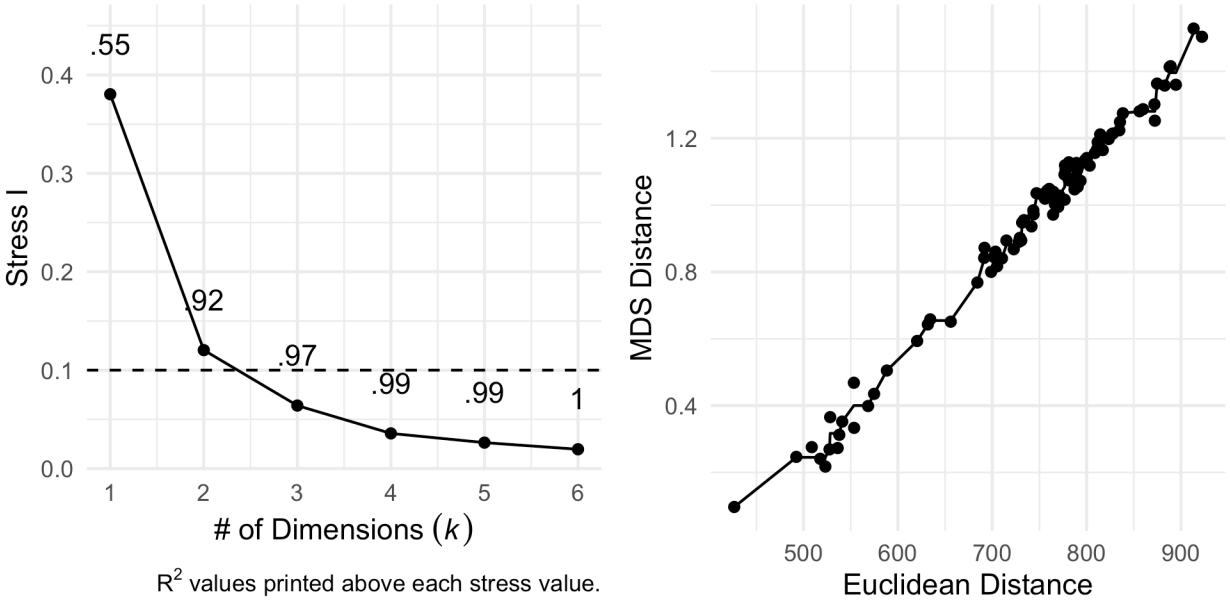


Figure 5

MDS on All Respondents - Dimensions 1 & 2

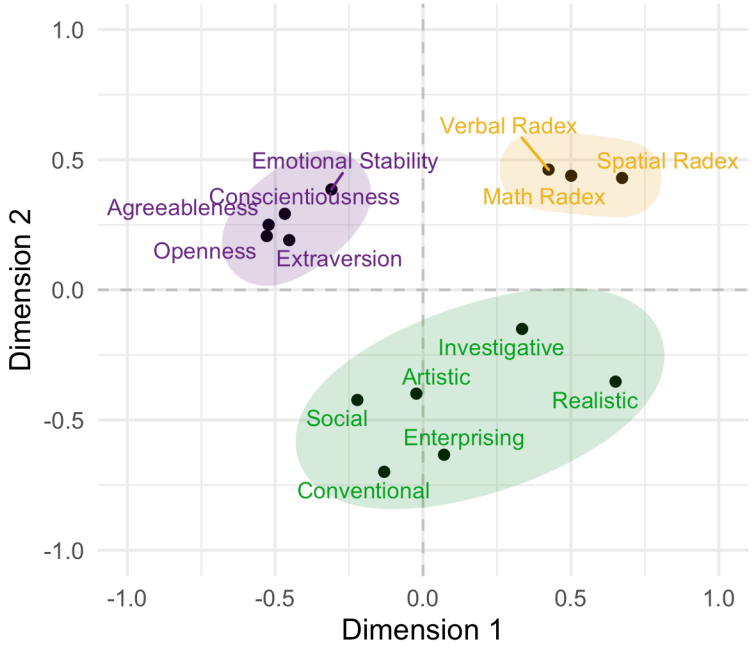


Figure 6

MDS on All Respondents - Dimensions 3 & 4

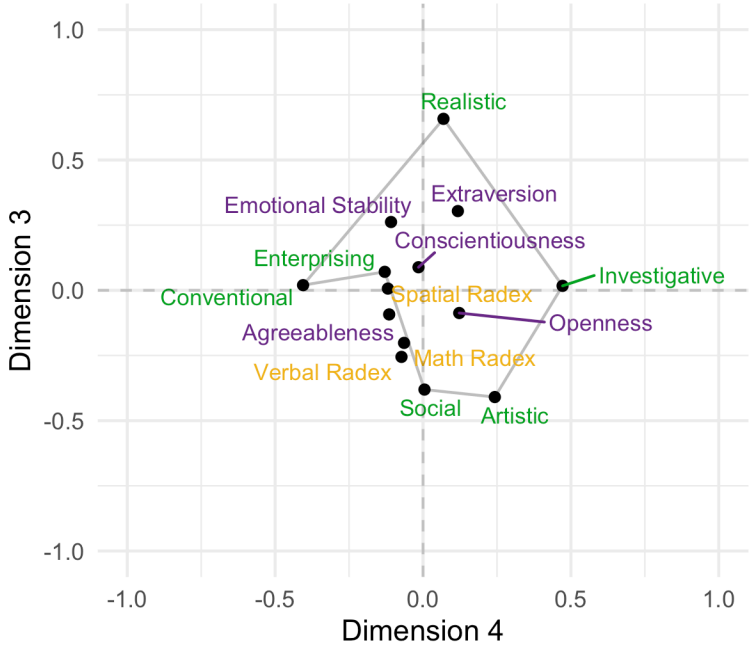


Figure 7

Female MDS - Dimensions 1 & 2

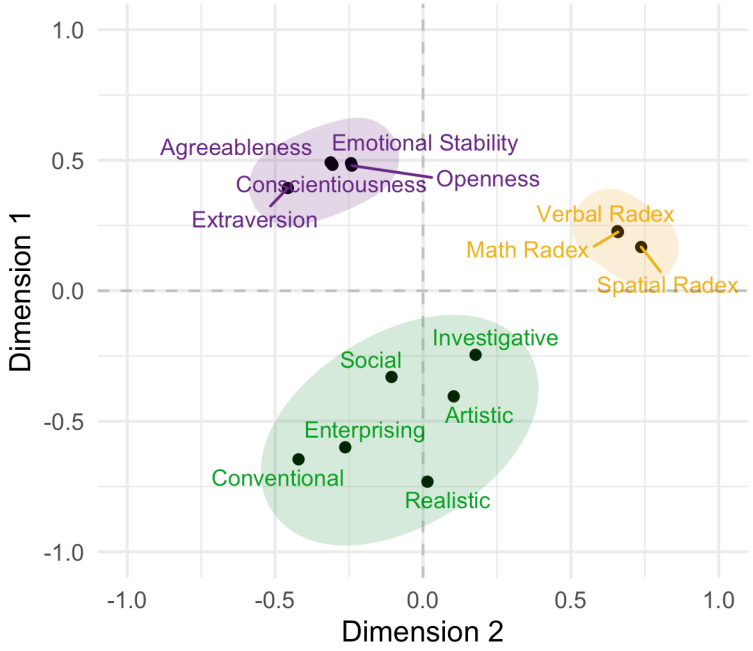


Figure 8

Male MDS - Dimensions 1 & 2

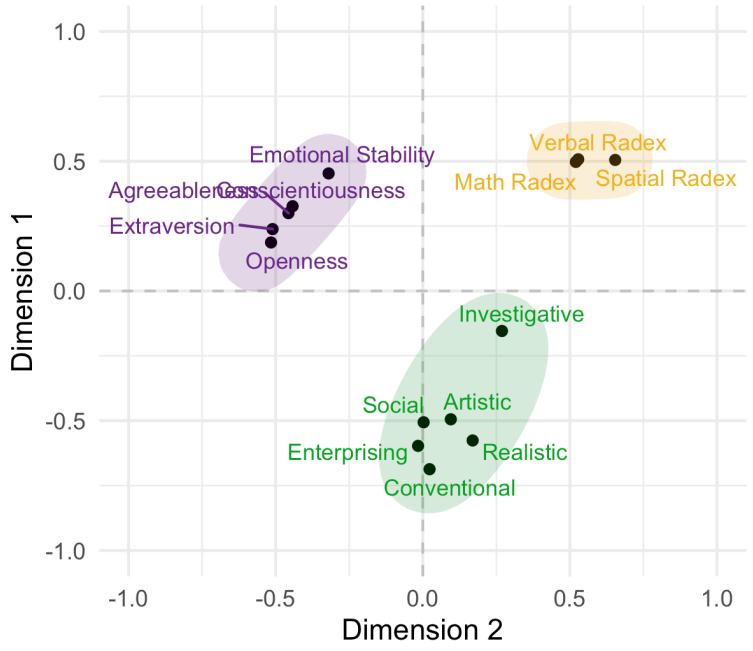


Figure 9

Female MDS - Dimensions 3 & 4

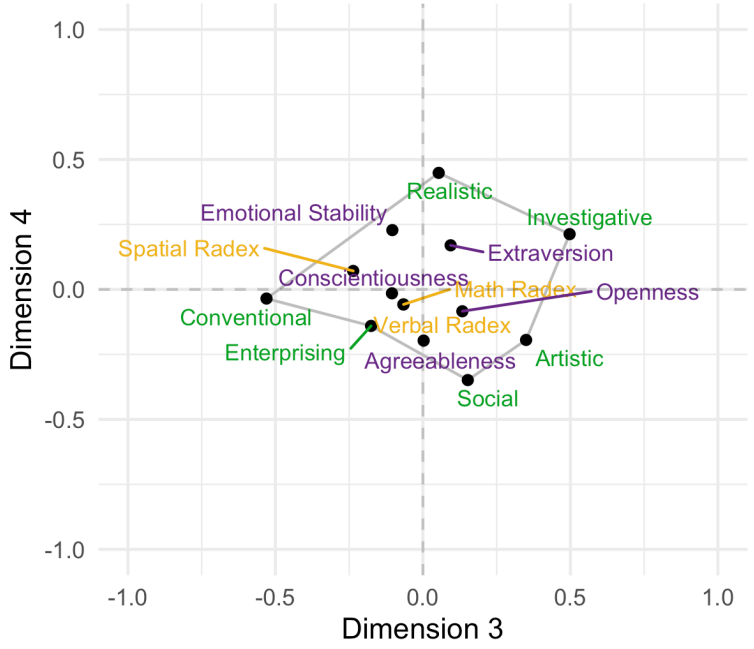
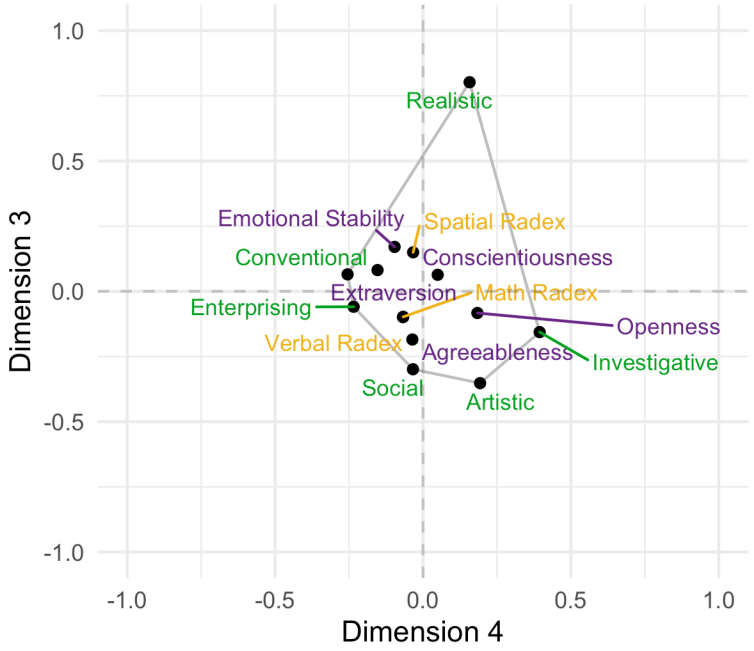


Figure 10

Male MDS - Dimensions 3 & 4



Judging by the MDS plots in Figures 5 and 6, the integrative dimensions in this study (i.e., dimensions 3 & 4) do not coincide with Hogan's (1983) Sociability & Conformity dimensions. Rather, they more faithfully represent Prediger's (1982) People-Things & Data-Ideas dimensions (with the caveat that both Enterprising and Conventional interests have slightly aberrant locations in the RIASEC hexagon).

H1b posited that with the addition of abilities, Hogan's Sociability dimension would account for more variance than the Conformity dimension. The People-Things dimension (i.e., dimension 3) was extracted before the Data-Ideas dimension (i.e., dimension 4) meaning that it accounts for more variance. Because People-Things is closer to Hogan's Sociability dimension than it is to Conformity, this could be construed as partial support for H1b. Because this dataset shows larger sex differences in interests than modern data (e.g., the difference between men and women in Realistic interests is $d = 1.81$), it is possible that the hexagonal structure is obscured in a full-sample MDS model. To assess this, Figures 7 through 10 show the results of two separate MDS models by sex.

Dimension 3 (i.e., the first integrative dimension) in the female MDS model (Figure 9) is akin to Data-Ideas. This comes closer to replicating the primacy of the Conformity dimension in Mount et al. (2005) than to supporting H1b in this study. Dimension 4 for women is a combination of Hogan's Sociability dimension and Prediger's People-Things dimension. Therefore, the MDS on women does not support H1b.

Dimension 3 for men (in Figure 10) lies between Hogan's Conformity and Prediger's People-Things. It bisects Conventional and Realistic interests at one end and Social and Artistic interests at the other. Dimension 4 runs from between Conventional and Enterprising on one end to between Realistic and Investigative at the other, so it does not bisect the hexagon cleanly.

Because the first integrative dimension for men is closer to Sociability than to Conformity, this model provides partial support for H1b.

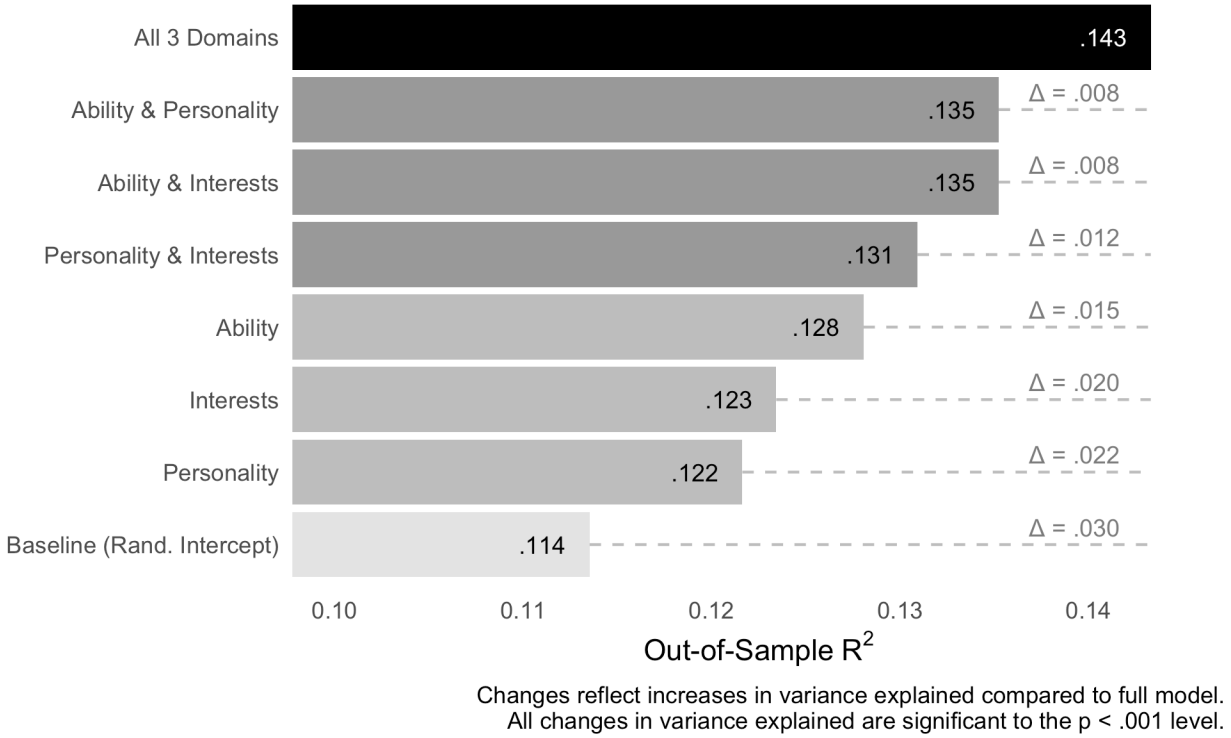
Overall, the full MDS model shows partial but weak and somewhat ambiguous support for H1b. Follow-up analyses split by sex suggest that the hypothesis is more defensible among men than women.

H2 - Incremental Predictive Validity

Hypotheses 2a-2c posited that each of the three individual difference domains would explain incremental variance in Work Satisfaction above and beyond the other two. Each construct within each domain is represented by the five typical polynomial regression terms in larger integrative equations. To assess the predictive validity of each model and to control for the influence of outliers in this relatively flexible polynomial regression model, out-of-sample R^2 was computed through 10-fold cross-validation. Figure 11 shows the specific R^2 values and the changes in R^2 when comparing any subset model to the full model. Pairwise comparisons adjusted with a Tukey test confirm that adding each of the three individual difference domains to a model that already contains the other two (along with a random intercept) does explain incremental out-of-sample variance in Work Satisfaction. Therefore, hypotheses 2a-2c are supported.

Figure 11

Changes in Predictive R^2 Between All Possible Subsets and the Full Model

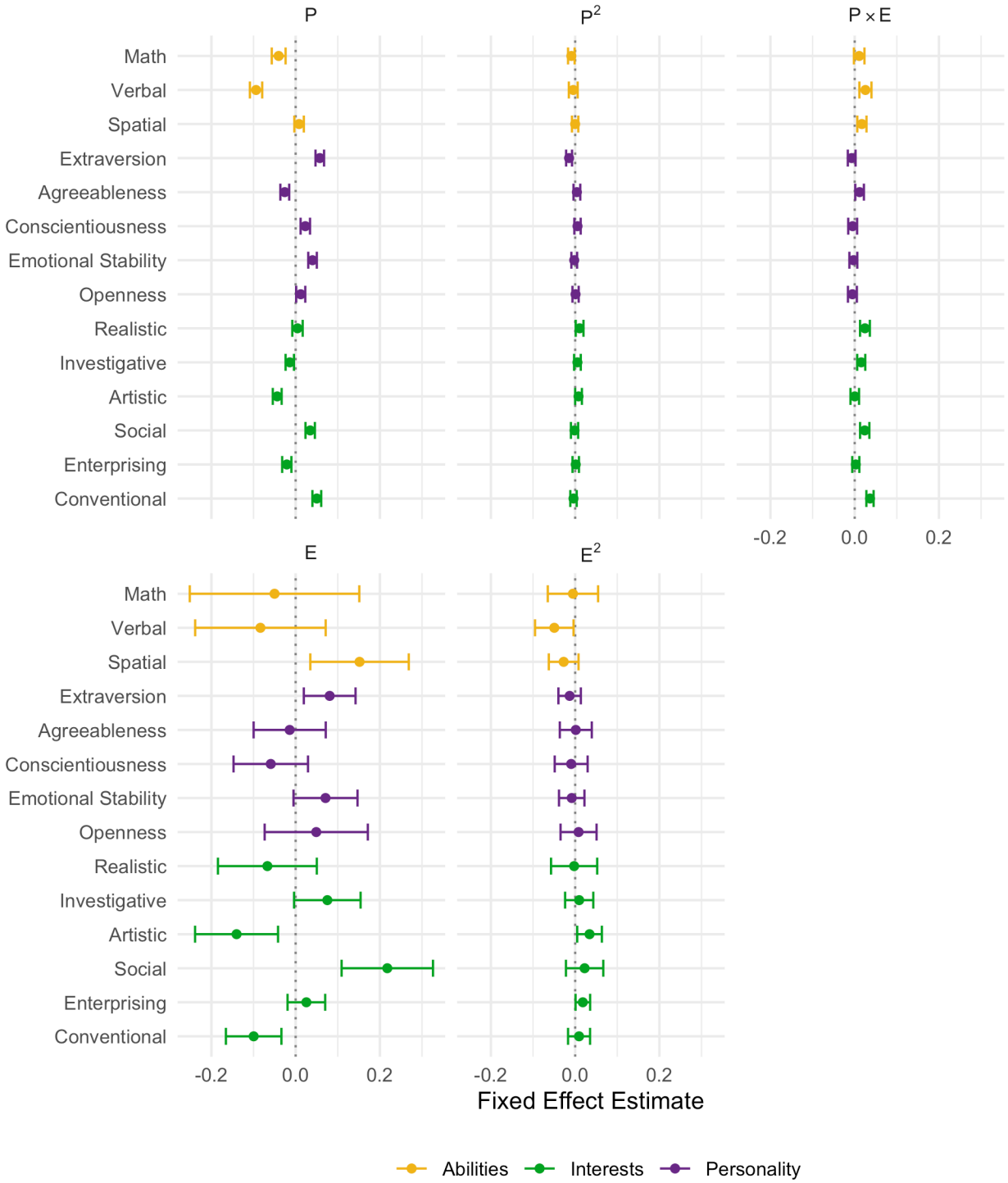


H3 - Importance of Fit Across Domains

Coefficients and their confidence intervals for each term in the full polynomial regression model are shown in Figure 12. Note that while the estimates for the Environment terms have the highest magnitudes, they also have the most uncertainty. Among those Environment estimates, interests appear to have the strongest main effects: Artistic and Conventional have negative effects and Spatial, Extraversion, and Social have positive effects. The squared Environment terms have relatively high magnitudes as well but with even more uncertainty than the main Environment effects. Among Person effects, Verbal ability has a relatively strong negative effect on Work Satisfaction, while the others are typically below .05 in magnitude. Lastly, interests have slightly more positive interaction effects than the other two domains.

Figure 12

Fixed Effect Estimates from the Full Polynomial Regression Model



Error bars represent 95% confidence intervals.

Relative Importance Analysis

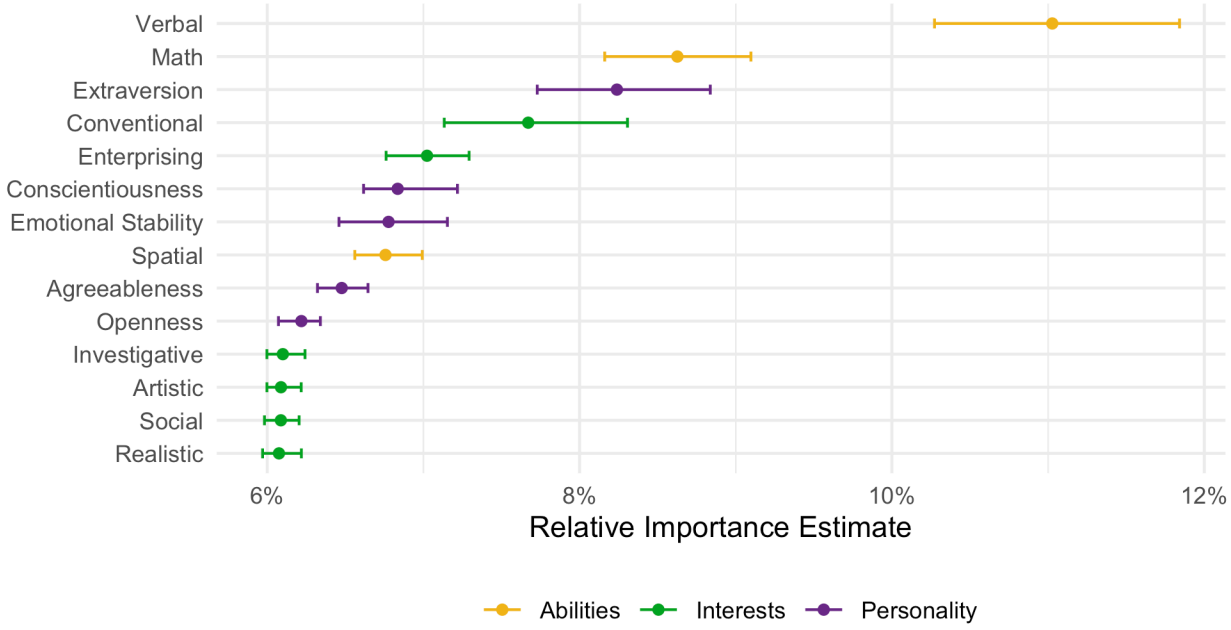
Another way to assess the relative contributions of the three domains is to build an ensemble model from their respective predictions. In this case, a 5-term polynomial regression model was trained for each construct individually. The predictions of Work Satisfaction generated from each of those models were then used as predictors in an ensemble model which was used to generate estimates of relative importance, both at the construct and domain levels.

Of the three domains, abilities had the highest relative importance (36.4%) followed by personality (32.6%) and then interests (31%). Bootstrapping these weights reveals that all three pairwise differences between these domain importance estimates were significant at the $p < .05$ level. This pattern of relative importance across domains is the opposite of the order that was hypothesized, so operationalizing fit importance as relative importance in an ensemble model does not support H3.

To understand importance *within* each of these domains, Figure 13 shows estimates of the relative importance of each construct in the study. Note that Verbal ability is substantially more important than others, and Math ability is the second most important construct.

Figure 13

Comparison of Relative Weights Across Constructs



Response Surface Analysis

H3 stated that interest fit would be the most important with personality being second and ability being the least important. The underlying assumption in this study is that more congruence between person and occupation should be associated with higher Work Satisfaction. For fit to be more important in one domain compared to another, fit must have a more positive association with Work Satisfaction across constructs. Because fit cannot be captured in a single metric and then simply correlated with an outcome, response surfaces and the parameters which describe them must be used as proxies to understand the nature of fit relationships.

For each individual difference construct in this study, there are two surface plots below as part of Figure 14. The first, labeled “Individual” is built from the coefficients of a polynomial regression model using only the terms associated with that construct in addition to an intercept. For example, the “Individual” plot for Math ability predicts Work Satisfaction with the following

equation: $WS = b_0 + b_1 P_{Math} + b_2 E_{Math} + b_3 P_{Math}^2 + b_4 P_{Math} E_{Math} + b_5 E_{Math}^2$. The second plot for each construct, labeled "Integrative", is built from coefficients produced by the single, large polynomial regression model which includes 5 terms for each construct (i.e., 14 constructs produce a total of 70 fixed effects). The same 5 coefficients (plus an intercept) are used to construct the plots, but in this case, the coefficients are conditional on all other constructs in the model. That is, they represent the effect of each construct when every other value is held constant.

In each plot, the blue line represents the line of congruence (LOC) at which $P = E$, the red line is the line of incongruence (LOIC) when $P = -E$. Because environment scores represent the mean trait level of people in each occupation, the ranges of environment scores are necessarily restricted compared to person scores. Thus, the axes in all plots below do not have equal lengths, and the LOC and LOIC do not appear perpendicular as they typically do.

Figure 14

Response Surfaces for All Constructs

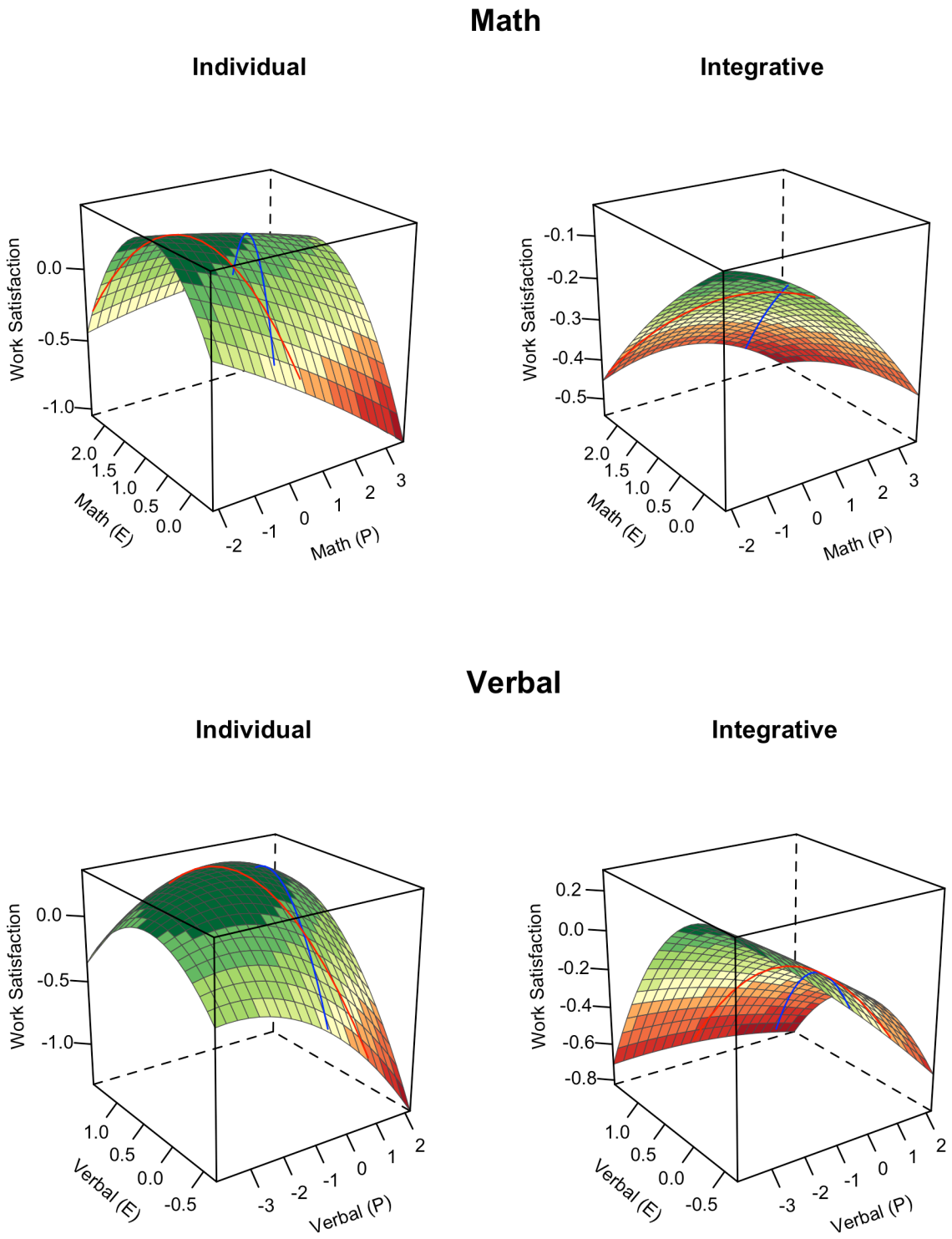
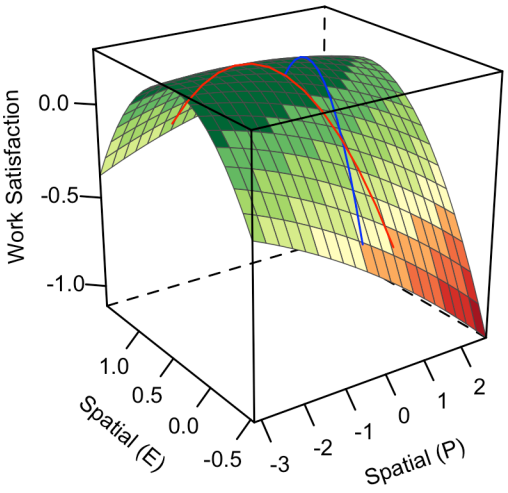


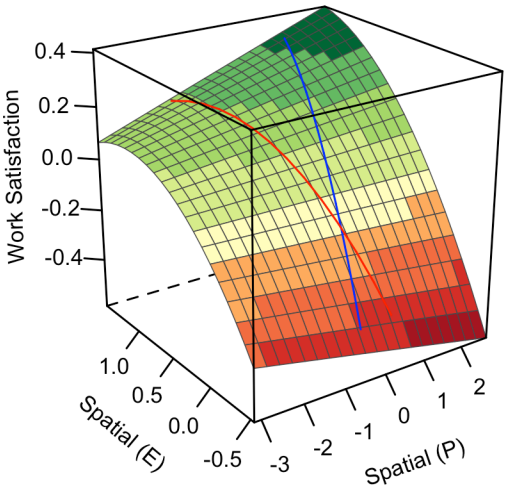
Figure 14 (cont'd)

Spatial

Individual

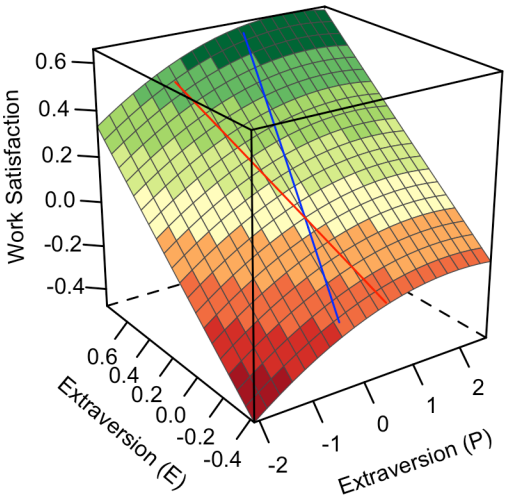


Integrative



Extraversion

Individual



Integrative

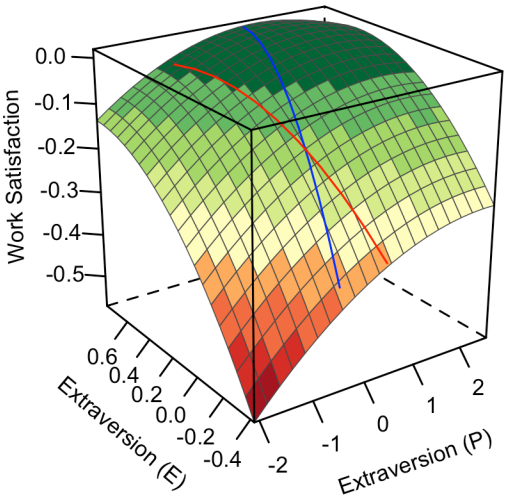
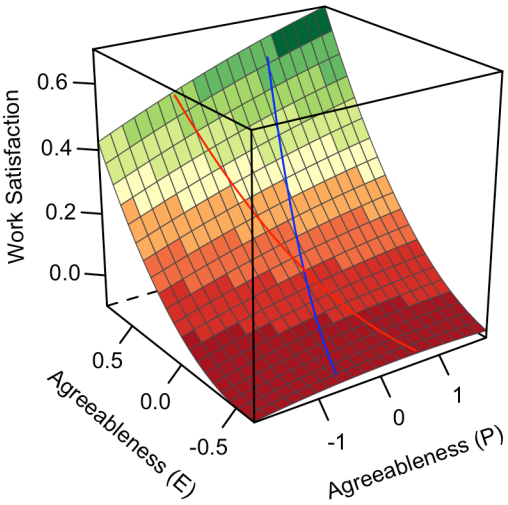


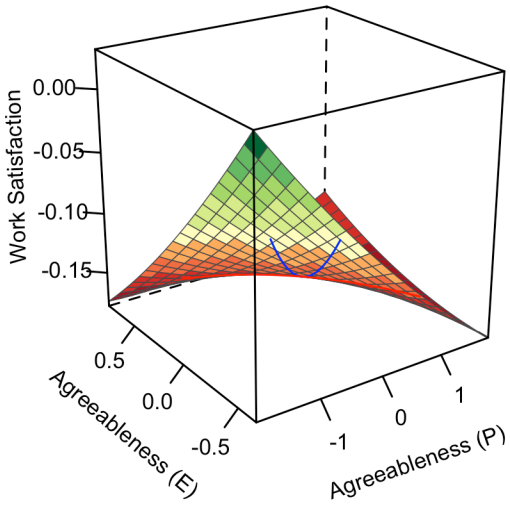
Figure 14 (cont'd)

Agreeableness

Individual

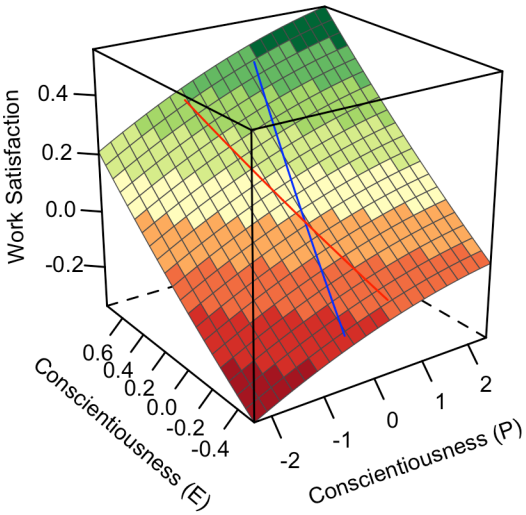


Integrative



Conscientiousness

Individual



Integrative

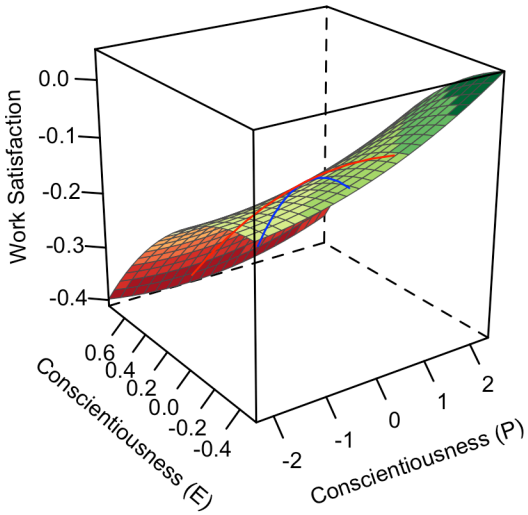
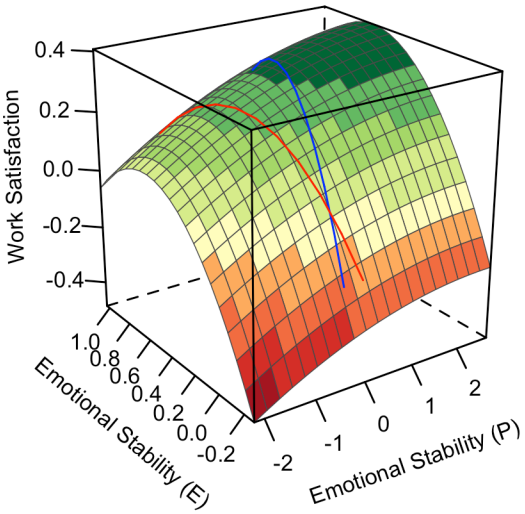


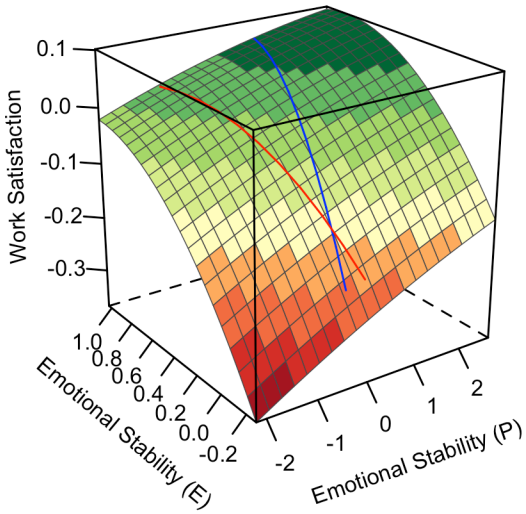
Figure 14 (cont'd)

Emotional Stability

Individual

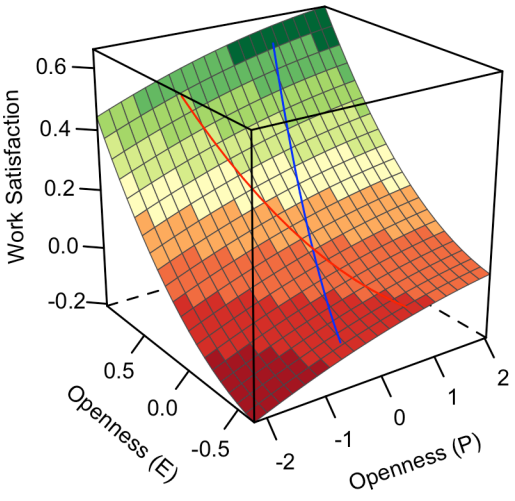


Integrative



Openness

Individual



Integrative

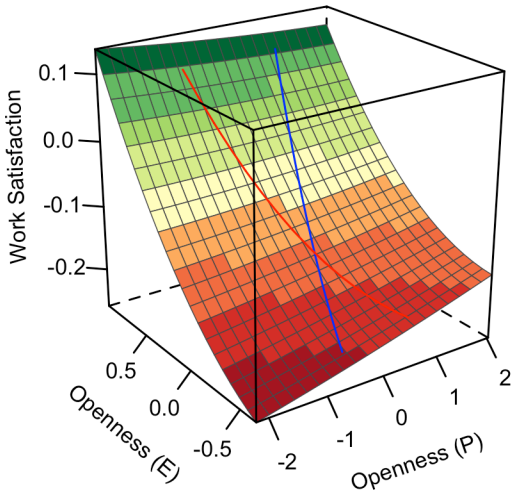
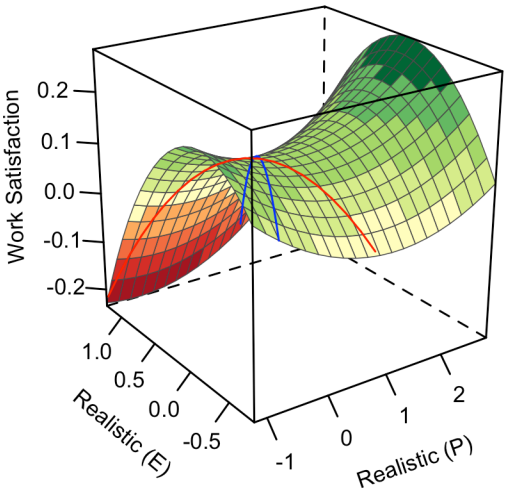


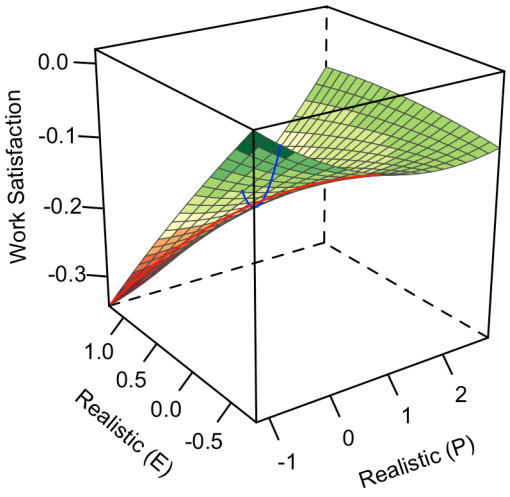
Figure 14 (cont'd)

Realistic

Individual

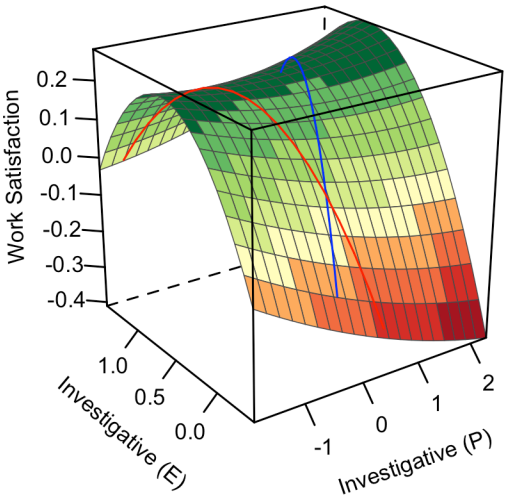


Integrative



Investigative

Individual



Integrative

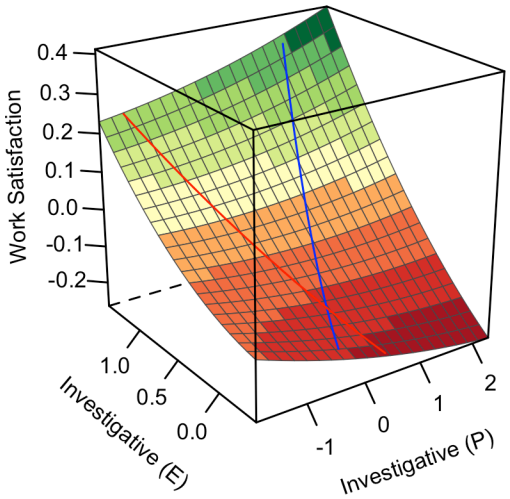
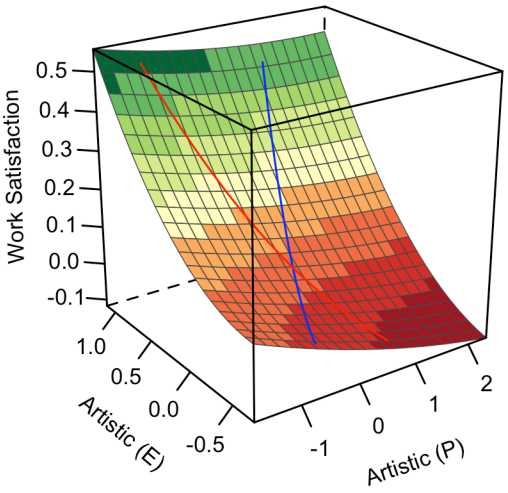


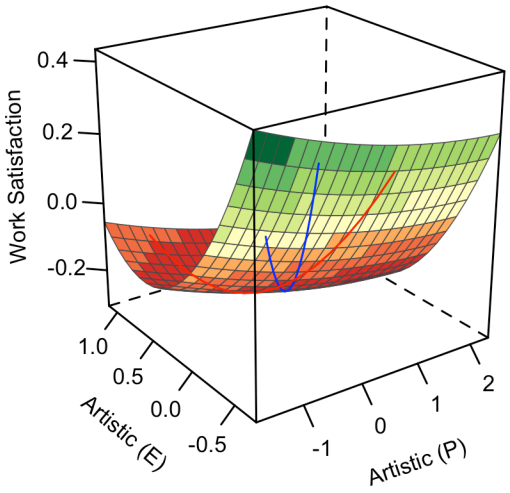
Figure 14 (cont'd)

Artistic

Individual

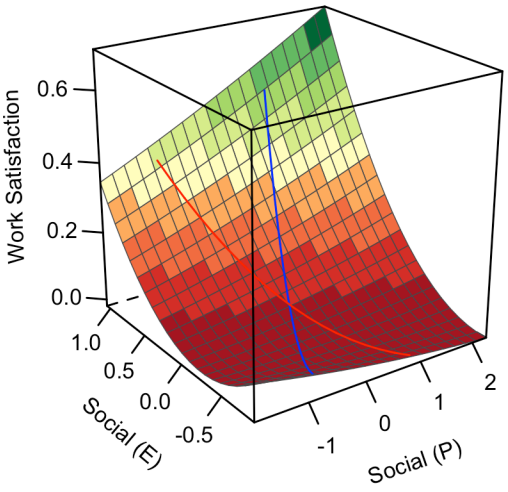


Integrative



Social

Individual



Integrative

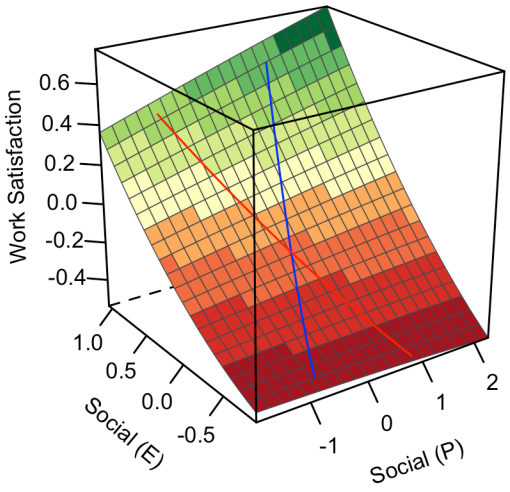
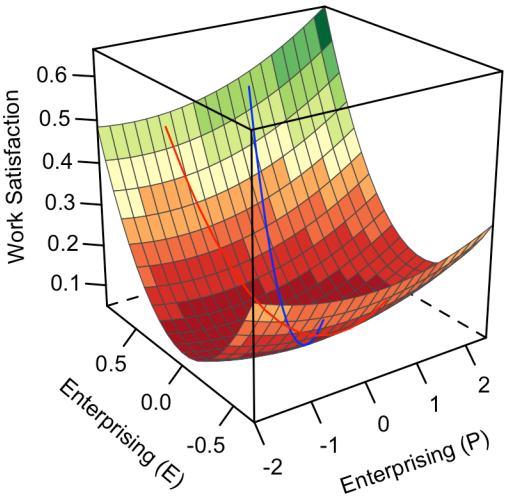


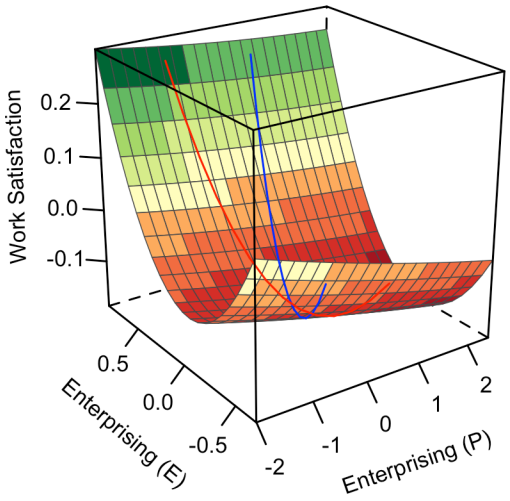
Figure 14 (cont'd)

Enterprising

Individual

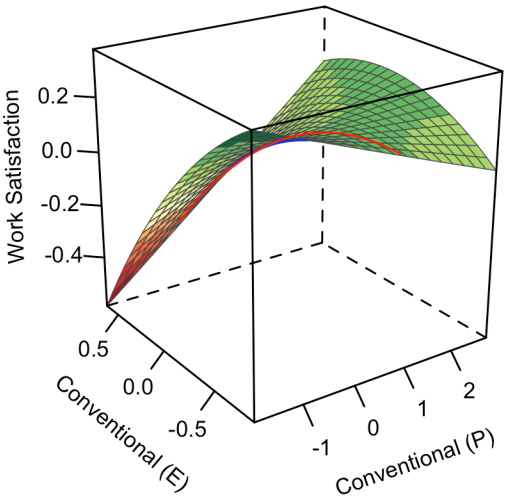


Integrative

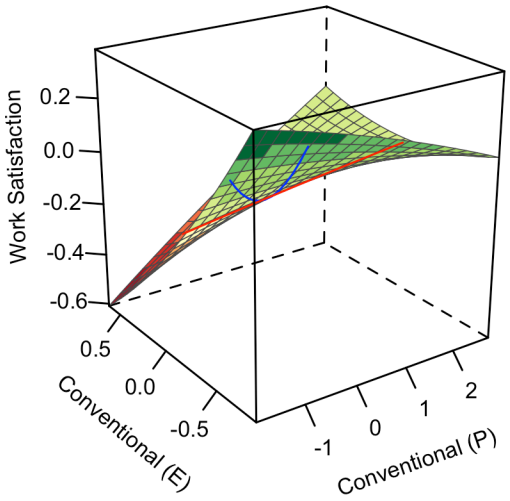


Conventional

Individual



Integrative



Tables 6 and 7 show the surface parameters for individual models and the large integrative model, respectively. As previously mentioned, broad congruence is indicated when a_5 is not significantly different from zero (i.e., satisfaction tends to be maximized along the LOC), a_3 has a negative value (i.e., an inverted-U shaped curvature along the line of misfit), and a_4 is near zero (i.e., the slope along the line of misfit is flat when $P = E$). This means that along any line parallel to the LOIC, Work Satisfaction tends to peak when congruence is high and trail off with more incongruence. No construct in either the individual or integrative models satisfies these criteria, so there is not sufficient evidence for either a broad or a strict congruence effect in these data according to the aforementioned criteria from Nestler et al. (2019).

To summarize, operationalizing fit importance as the relative importance of each domain in an ensemble regression does not support the hypothesized pattern of importance in hypotheses 3a and 3b since the opposite pattern emerged: abilities > personality > interests. Because main effects can account for the relative importance of a domain in an ensemble model, interpretation of response surfaces is also necessary to understand fit more fully. Response surface analyses showed that none of the constructs met the criteria for the congruence relationships described by Nestler et al. (2019) in which fit is associated with a higher value on the outcome. This does not mean that there is no evidence of congruence effects whatsoever, and the Discussion includes a more nuanced interpretation of the response surfaces. However, neither fit operationalization supports the hierarchy of importance posited in hypotheses 3a and 3b.

Table 6

Surface Parameters for Each Construct in the Individual Models

Construct	a_1	a_2	a_3	a_4	a_5
Math	.58***	-.3***	-.84***	-.44***	.35***
Verbal	.52***	-.3***	-.84***	-.52***	.35***
Spatial	.66***	-.47***	-.87***	-.67***	.55***
Extraversion	.73***	-.02	-.57***	0	-.03
Agreeableness	.46***	.33	-.39***	.24	-.3
Conscientiousness	.51***	.06	-.39***	.04	-.06
Emotional Stability	1***	-.77**	-.88***	-.8**	.76**
Openness	.39***	.19	-.29***	.19	-.21
Realistic	-.05	-.15	.02	-.23**	.23**
Investigative	.52***	-.31**	-.61***	-.44***	.39***
Artistic	.2**	.16	-.27***	.13	-.13
Social	.24***	.26*	-.19***	.15	-.2
Enterprising	.09	.57*	-.07	.52	-.52
Conventional	-.34***	-.07	.46***	-.38	.23

* $p < .05$, ** $p < .01$, *** $p < .001$

Table 7

Surface Parameters for Each Construct in the Integrative Model

Construct	a_1	a_2	a_3	a_4	a_5
Math	-.13	-.01	.03	-.05	.01
Verbal	-.13	-.22	-.1	-.34*	.27*
Spatial	.55**	-.15	-.57**	-.24	.2
Extraversion	.45**	-.33	-.33*	-.27	.27
Agreeableness	-.08	.07	.03	-.02	-.02
Conscientiousness	-.21	-.18	.25	-.14	.18
Emotional Stability	.42	-.21	-.34	-.18	.19
Openness	.19	.08	-.16	.12	-.09
Realistic	-.13	.05	.12	-.04	.02
Investigative	.16	.13	-.21	.04	-.07
Artistic	-.43**	.34*	.35*	.34*	-.32*
Social	.57***	.18	-.49***	.07	-.13
Enterprising	.07	.49*	-.11	.46*	-.47*
Conventional	-.31*	.27	.42**	-.01	-.14

* $p < .05$, ** $p < .01$, *** $p < .001$

H4 - Higher-Order Predictors

An MDS model produces coordinates on each dimension for each construct. Therefore, to construct these higher-order predictors, these coordinates were used to compute four weighted averages from scaled predictors, one for each of the four MDS dimensions. Figures 5 and 6 show the four dimensions extracted in the overall MDS model. Conceptually, these dimensions can be described with the following labels.

1. Cognitive (vs Non-Cognitive)
2. Ability & Personality (vs Interests)
3. Things (vs People)
4. Ideas (vs Data)

Average predictive R^2 across folds for a polynomial regression model using higher-order predictors was 0.138 for Work Satisfaction and 0.114 for Job Satisfaction. This difference is statistically significant at the .001 level. Thus, a model using higher-order predictors constructed from MDS coordinates predicts Job Satisfaction worse than it does Work Satisfaction, and H4 is not supported.

Environmental Variation

Most PE fit research examines the congruence of mean scores of person and environment. Someone with a mean Extraversion score of 4 in an occupation with a mean Extraversion score of 2 has an absolute difference from the occupation of 2. However, this says nothing about whether this two-unit difference is big or small in relation to other people in that occupation. It says nothing about the practical significance of the distance. If everyone else in the occupation is clustered tightly around that environmental mean (i.e., a low environmental variance), then an absolute difference of 2 might be considered a substantively poor fit. Conversely, if colleagues' scores vary widely and produce a high environmental variance, then the same 2-unit difference might be relatively common and inconsequential. The high sample size and diversity of occupations in Project TALENT supports a more robust operationalization of environmental variance than most samples.

Edwards (1993) shows how polynomial regression can be seen as, essentially, a squared difference score which also includes main effects for the person and the environment. To incorporate environmental variation, one could imagine a polynomial regression equation that is an extension of a squared z-score in which that difference is contextualized by the standard deviation of the environment. In this study, environmental variation (σ_j) will be examined as a

continuous moderator using the following equation: $Z_{ij} = b_0 + b_1 P_{ij} + b_2 E_j + b_3 P_{ij}^2 + b_4 P_{ij} E_j + b_5 E_j^2 + b_6 \sigma_j + b_7 \sigma_j P_{ij} + b_8 \sigma_j E_j + b_9 \sigma_j P_{ij}^2 + b_{10} \sigma_j P_{ij} E_j + b_{11} \sigma_j E_j^2 + u_{0j}$.

The presence of a moderation effect was tested by assessing whether or not the additional terms above add incremental out-of-sample R^2 to the original equation. Overall, the moderated model has an R^2 that is not higher than the baseline polynomial model. Therefore, these data fail to support the notion that environmental variation moderates fit.

DISCUSSION

This study built on prior research on individual differences and person-environment fit by integrating three of the most widely studied domains of individual psychological differences in a single, representative sample. Adding abilities to the design in Mount et al. (2005) allowed a more complete mapping of the individual difference territory. Additionally, compared to previous work, the inclusion of all three domains in both single-construct and full integrative models presents a novel and more exhaustive comparison of the importance of these domains in predicting future Work Satisfaction. Lastly, the unique sample allowed the operationalization of environmental variation which was examined as a moderator to the core model.

Mapping Individual Differences

Hypothesis 1a posited that the non-cognitive characteristics, personality and interests, would be more closely related to each other (i.e., have lower Euclidean distances) than to cognitive abilities. This hypothesis was not supported. The correlation matrix in Figure 3 showed that while interest and personality correlations are almost exclusively positive (except for Realistic interests), the magnitudes of the correlations were somewhat lower than those found in recent meta-analyses. For example, the correlation between Extraversion & Enterprising was .16 in the present study compared with .41 reported in the Larson et al. (2002) meta-analysis. Similarly, the correlation between Artistic interests and Openness was .29 in this study compared to .48 reported by Larson et al. (2002). One other potential reason for the lack of significant differences in inter-domain distances is that interests showed slightly closer relationships with ability than research typically suggests. For example, Pässler et al. (2015) found slightly negative relationships between both Social and Enterprising interests with general intelligence, but these relationships were slightly positive in this study.

Abilities typically correlate positively with Investigative interests and negatively with Enterprising interests. Therefore, it was reasonable to expect, as hypothesis 1b states, that adding abilities to the personality-interests model in Mount et al. (2005) would make the Sociability dimension more important since it runs from Investigative to Enterprising interests. In general, this hypothesis was not supported by the data.

One reason that the integrative dimensions produced in the MDS (i.e., dimensions 3 & 4) differed from those in Mount et al. (2005) is that the RIASEC hexagon did not emerge until the third dimension. In Mount et al. (2005), dimensions 2 & 3 created the RIASEC hexagon, so only the relationships explained by dimension 1 had been partialled out. In this study, the variance of two dimensions had already been partialled out before examining the RIASEC dimensions. For example, the high correlation between Investigative interests and abilities is already accounted for in dimensions 1 and 2, so the integrative dimensions actually place abilities relatively far from Investigative interests belying their relatively strong zero-order correlations. Beyond substantive differences in the data between this study and Mount et al. (2005), this partialling effect could have skewed the results in ways that would have been difficult to anticipate beforehand.

The MDS analyses in the present study, both overall and split by sex, all supported the primacy of Prediger's (1982) People-Things dimension rather than Hogan's (1983) Sociability or Conformity dimensions. Because H1b presupposed the extraction of Hogan's dimensions, it could only be evaluated according to which of Hogan's dimensions were closer to the extracted dimensions. As mentioned previously, the Sociability dimension explains more variance than the Conformity dimension for men than it does for women. Because women have relatively low levels of Realistic interests overall, this restricted range may account for the lack of importance

in this dimension. Conversely, Openness and Artistic interests are more closely related to abilities in women than in men, and this may partially explain why the Data-Ideas dimension was extracted first.

Predicting Satisfaction

The baseline model which only included an intercept allowed to vary between occupational groups explained 11.4% of the variation in Work Satisfaction. Interestingly, a full model which includes all the polynomial regression terms (i.e., 5 terms each for 14 constructs) *without* the random intercept explains roughly the same amount of variance. This indicates that there is substantial variation in Work Satisfaction between occupations. This information alone might be relevant to career choosers who are curious what the typical levels of satisfaction are for people who have already chosen and gained experience in a particular field.

Combining those two models (i.e., adding the polynomial regression terms to the random intercept model) accounts for an additional 3% of out-of-sample variance in Work Satisfaction, and this difference is statistically significant. While knowing someone's occupation accounts for a majority of the predictive validity, knowing someone's psychological characteristics in high school and those of their colleagues does add incremental validity. Additionally, as the support for H2a-H2c suggests, each domain added significant incremental predictive validity to a model with the other two domains with abilities adding slightly more than personality or interests.

The ability domain had the highest relative importance in the ensemble model followed by personality and then interests. This order echoes a previous study using Project TALENT data which found that abilities were more predictive of occupational attainment than interests (i.e., Austin and Hanisch, 1990). In the current study, the response surfaces for the individual models of abilities (i.e., the models used in the ensemble) showed that their predictive validity was

primarily due to the curvilinear effects (i.e., inverted U-shape) of environmental ability on Work Satisfaction. That is, occupational satisfaction tends to be maximized when occupational ability is moderately high but decreases when it is too high or too low. In addition, occupations with very high ability levels (e.g., 1.5 or more SD above the grand mean) tend to have noticeably lower levels of satisfaction. It is possible that people with high ability feel like they could have chosen from among a wide variety of occupations. This could increase the likelihood of experiencing overchoice syndrome (Rysiew et al., 1994) in which high ability individuals continually wonder if they should have chosen differently from their seemingly unlimited options for a career.

Lastly, including environmental variation as a moderator to congruence relationships did not explain incremental variance beyond occupational membership and the person and environmental scores. It may be worth noting that a model which did not include occupational membership as a control (i.e., a random intercept) did show marginal improvement when environmental SD was added as a moderator. However, this effect disappeared in the final and more appropriate multilevel model. While these data do not support the variability of the environment as a moderator, the rationale behind it remains valid, so future investigations using these traits and others (e.g., PE fit on values) are worth exploring.

Higher-Order Predictors

A polynomial regression model using dimensions created through multidimensional scaling did not predict Job Satisfaction better than Work Satisfaction. In addition to the Work Satisfaction items which focus on the work itself, the Job Satisfaction scale included a variety of other types of satisfaction (e.g., pay, security, coworkers, etc.). It is possible that this high-bandwidth measure had too much intra-construct variation or even construct contamination. This

could have prevented prediction at the same level as Work Satisfaction which is a purer construct. Using the four MDS dimensions as polynomial regression predictors only explained slightly less out-of-sample variance than using all of the original 14 individual difference constructs. In this study, both models required the same granular measurements. However, these results suggest that a smaller number of broader scales (e.g., general mental ability, interest in people, interest in things) might predict satisfaction with only slightly degraded accuracy and significantly greater parsimony.

Congruence Hypotheses

After controlling for occupation, none of the constructs in this study showed evidence of an exact form of congruence as defined by Nestler et al. (2019). However, response surfaces do not need to show the ideal saddle shape maximized along the LOC to support a congruence effect. For example, while the integrative Extraversion plot has a relatively steep slope along the line of misfit, satisfaction tends be maximized as P and E increase together along their ranges (even if satisfaction is not maximized along the LOC). While the integrative Math plot's α_4 is not statistically significant, the overall pattern of surface parameters supports a subtle saddle shaped congruence effect. The magnitudes of coefficients in the integrative Agreeableness plot are very small, so the surface parameters are not significant, but satisfaction appears to be maximized along the LOC nonetheless. Lastly, the integrative Conventional plot shows a slanted saddle in which $P > E$ is associated with higher satisfaction than when $E > P$. These deviations from the ideal saddle shape suggest, as Edwards (2002) did, that there may be more than one type of congruence hypothesis. For example, Wiegand (2018) examined misfit asymmetry in which one type of misfit is associated with higher levels of the outcome than the other. People might satisfice such that when they reach a level of fit that is good enough, the marginal change

in satisfaction from seeking better fit is negligible or even negative. Future research might benefit from a systematic classification of fit styles, each with its own criteria for detection with response surface parameters.

Some more specific patterns emerged in the response surfaces as well. In four of the six ability plots (i.e., two for each construct), the lowest predicted level of satisfaction occurs when P is very high and E is very low. This type of misfit appears more detrimental than its opposite, and this lends credence to the notion that people do best when work is as complex and rewarding as their abilities allow. However, as discussed previously, this effect is due primarily to the environment, so congruence at very low and very high levels of ability produce mediocre satisfaction predictions. Realistic and Conventional interests show the opposite pattern of abilities in this respect. The two interests have minima when E is high and P is low suggesting that environmental excess is substantially more deleterious than personal excess. It is possible that occupations with very high Realistic or Conventional Interests may be less rewarding (e.g., manual labor or repetitive work). Another contrast with the ability pattern is that Realistic and Conventional interests are U-shaped along the LOC suggesting that congruence at high and low levels of these constructs may be preferable to fit at moderate levels. Lastly, Extraversion, Emotional Stability, and Openness all tend to show independent effects of P and E with more of each typically being better than less. Thus, having higher levels of these personality traits is beneficial on its own, and occupations with higher mean levels tend to have higher satisfaction.

Most of the constructs showed patterns that were generally similar in the individual and integrative models. While collinearity is a concern, these instances of correspondence in both plots lead to greater confidence in these findings. Notable exceptions are Agreeableness, Conscientiousness, and Artistic interests. These constructs show particularly high environmental

intercorrelations which likely account for the significant changes when moving from individual to integrative surfaces. Thus, surface patterns for these constructs are more uncertain and more contextually dependent than others.

Overall, environment effects were stronger than person effects in the present study. For example, the plots from the individual models for personality all show substantially more surface movement (i.e., linear and/or curvilinear effects) across the Environment axis than the Person axis. Extraversion is an example of a construct in which both person and environment are important. Particularly in the integrative model, satisfaction tends to increase linearly as both person and environment Extraversion scores increase, suggesting substantive main effects for both P & E but little to no interaction.

Incidentally, this pattern of the environment accounting for more variation in satisfaction is even more pronounced in models which do not allow the intercept to vary by occupation, presumably because the shared environment scores among people in the same occupation serve as a proxy for their shared environment and, therefore, show stronger associations with satisfaction. Even in the random intercept model, the fact that environment scores were built based on occupational membership means that they are technically more temporally proximal to the outcome measurement. It is possible that this accounts for some of the predictive advantage of environment over person variables.

Theoretical & Practical Implications

Broadly, this study echoes findings which emphasize the importance of the environment in determining Work Satisfaction (e.g., Dalal et al., 2013; Nye, Prasad, et al., 2018; Törnroos et al., 2019). Temporarily ignoring the limitations of this study which will be discussed below, the results here support the notion that some occupations are more likely to have employees who

report high levels of satisfaction with the work than others. Satisfaction may depend more on the provisions and characteristics of a job than on a person's idiosyncratic congruence with it. Tinsley (2000) mentions that "present status" models, which ignore person characteristics and focus exclusively on the supplies and/or demands of the environment, often predict outcomes like satisfaction and performance just as well as fit models. Job characteristics theory (Hackman & Oldham, 1975) stresses the importance of key provisions from the job like worthwhile tasks, feedback from the work, and use of a variety of skills in the determination of Job Satisfaction. Each of these is a characteristic of the work itself, however, rather than an aspect of the broader job like coworkers or compensation. Obviously, optimizing for Work Satisfaction requires some consideration of what the work actually entails. If the core tasks and responsibilities required in an occupation are relatively simple and repetitive, then people in the occupation will be less likely to report that their work is challenging or interesting. This aligns with theories that question the utility of following one's passion and, instead, emphasize the accumulation of career capital which can "buy" more satisfying work (Newport, 2012).

In addition to aiming for career paths which reward valuable skills, career choosers may benefit from focusing on careers in which current employees are relatively satisfied. Gilbert (2006) highlights a variety of ways in which humans make bad predictions about what will make them happy in the future. One strategy he recommends to counteract poor prognostications is talking to people who have already explored a particular path. Career paths can certainly change within a generation, and such change is more likely and more rapid now than ever before. This should not suggest that individual differences cannot help with this decision. Certain types of people may be self-selecting into highly satisfying careers based on traits not measured in this study, and it is possible that these people would have reported higher Work Satisfaction

regardless of their career choices. However, qualitatively and quantitatively simulating a career path by learning about who has already walked it can be a valuable and low-cost form of career exploration.

Ganzach (1998) found that job complexity was rather strongly related to occupational satisfaction between jobs. While this current study does not focus on job complexity per se, participants with more advanced degrees do report higher levels of Work Satisfaction than people with less advanced degrees or none at all. Considering all corrected pairwise comparisons between 5 degree levels (i.e., no degree, high school diploma, bachelor's degree, master's or graduate professional degree, and doctorate or law degree), satisfaction rose with each new level and the only non-significant difference was between no degree and high school diploma. Additionally, the mean Work Satisfaction among Project TALENT's broadest occupational designation (i.e., 13 categories in total) shows that two groups stand out with notably higher Work Satisfaction levels: "Medical and Biological Sciences" and "General Teaching and Social Service". One group had a notably lower mean Work Satisfaction than the others: "General Labor Community and Public Service". This further supports the notion that building career capital in the form of skills and/or credentials can be used to join occupations which enjoy higher levels of satisfaction on average.

Limitations & Future Directions

Perhaps the most significant limitation in this study is the use of psychological characteristics measured in high school to operationalize the occupational environments eleven years later. Technically, this design can only examine congruence with similar others *in high school* rather than with similar others on-the-job. While the psychological characteristics measured in this study are relatively stable, research shows the they all change in both random

(e.g., in response to unpredictable life events) and normative ways. Focusing on the latter, fluid abilities tend to peak in adolescence and young adulthood, so it unlikely that these would change drastically between high school and one's late twenties (Tucker-Drob & Salthouse, 2011). However, almost all major personality traits change during this time with Social Dominance, Emotional Stability, Openness to Experience, and Conscientiousness, being among the largest expected (upward) changes (Roberts et al., 2006). While interests tend to stabilize earlier in life than personality, Investigative, Artistic, Social, and Enterprising interests all tend to rise from adolescence to adulthood (Hansen & Wiernik, 2018; Low et al., 2005).

Therefore, this study addresses the question "If someone chooses the same job as students who were psychologically similar during high school, will that similarity associate with higher ratings of Work Satisfaction?". This does not negate the usefulness of these data for career choice decisions, as students are likely to have a more accurate sense of how their psychological characteristics compare to fellow high school students than to those of working adults who are nearly 30 years old. Furthermore, the fact that environment still shows a greater association with Work Satisfaction than person characteristics after controlling for occupational membership suggests that this imperfect operationalization still has merit.

Given the age of the Project TALENT data, population-level trait change may also confound results. For example, the Flynn effect (Pietschnig & Voracek, 2015) refers to a global increase in scores on intelligence tests over the last century. Thus, the mean level of abilities in a more modern dataset could be noticeably higher. Complementarily, the complexity of jobs has risen since 1971. Wyatt (2006) showed that the proportion of the United States' labor force in professional and technical occupations went from roughly 15% in 1970 to just under 25% in 2000; this sector saw the largest increase in the 20th century overall. While the sample of jobs in

Project TALENT is broad, the occupational landscape has changed significantly since 1971, and the modern blend of jobs could have a significant impact on the relative importance of this study's focal domains and individual difference constructs.

Another significant social change since Project TALENT is that female labor force participation has continued to increase (i.e., from 43.3% in 1970 to 59.8% in 1998; Fullerton, 1999). Women made up 29.6% of the total workforce in 1950 and 46.6% in 2000 (Toossi, 2002). To the extent that sex differences in psychological characteristics remain (e.g., interest in Things vs. People), changes in the sex balance of specific occupations can shift the occupational distributions of traits. This study found a male-female difference on Realistic interests that is substantially higher than more modern meta-analytic estimates (Su et al., 2009), suggesting that the difference is inflated in this study, the difference has actually declined, or some combination of both. Regardless, the psychological profiles of occupations can certainly change with demographic changes in the broader workforce, and these changes could have affected the results of the present study.

Attempting to map Project TALENT measures and items to more modern psychometric frameworks introduced another significant limitation in this study. For example, Openness in this study suffers construct deficiency when compared to how it is typically conceptualized. The exclusive use of the PT "Culture" scale as a proxy for Openness as recommended by Pozzebon et al. (2013) may cover the Openness to Experience aspect of Openness, but it ignores the Intellect aspect (DeYoung, 2015). This deficiency translates into results: rather than being closely related to abilities as Openness typically is, it is the farthest personality scale from the ability cluster in the overall MDS model (with the caveat that this is only the case with men, as the female MDS shows the expected proximity to abilities). Given the focus of the PT Culture scale, it is possible

that high ability women were more likely to channel those abilities to more cultural predilections.

This study focused exclusively on supplementary fit or how people compare to others in the same occupation. If people gather information on their own strengths and predilections by comparing themselves to others, it is reasonable to expect that an individual will choose a career based on whether or not he or she is similar to the typical person in that occupation. However, future research would benefit from examining complementary fit as well. Rather than examining whether other people in the occupation share similar psychological characteristics, future studies could operationalize the person and the environment congruently (e.g., using the TWA measurement paradigm) and focus on the opportunities or requirements for various psychological traits in different occupations.

In addition to addressing the design limitations of this study, future research could benefit from the incorporation of work values as a fourth domain. Broadly, Rokeach (1973) conceptualized values as beliefs that provide standards by which people can evaluate the desirability of both means and ends. While vocational interests focus on liking or disliking of certain work activities, work values focus on a person's beliefs about what is important or unimportant in their work. This evaluative component is obviously relevant to career choice. Values associate with both personality (e.g., Openness and Autonomy; Furnham et al., 2005) and interests (e.g., Enterprising interests and self-enhancement values; Sagiv, 2002). Values have a strong theoretical background in PE fit research (e.g., Dawis, 2005), and evidence suggests that values fit may be more important in determining satisfaction than interest fit (Earl, 2014).

There is also a noticeable overlap between values and the job characteristics, broadly construed, which enable satisfying work. For example, Leuty & Hansen (2011) ran a PCA on

various work values measures and landed on the following factors: (1) achievement, (2) relationships, (3) autonomy, (4) environment, (5) organizational culture, and (6) status. These are all relevant to satisfaction with one's job broadly. Autonomy, in particular, is related to Job Satisfaction and internal work motivation (Humphrey et al., 2007), so the extent to which an occupation can meet someone's desired level of autonomy is relevant to career choice and future Work Satisfaction.

One challenge to using values to inform career choice in high school is that they do not stabilize until early adulthood, and people tend to emphasize intrinsic values early in life but gravitate to more extrinsic values as they age (Rounds & Jin, 2012). Thus, values might be more effective for people who have gained some work experience and have a more mature sense of what is important in work (e.g., undergraduate and graduate students or mid-career changers).

Conclusion

Results of this study support the primacy of Prediger's (1982) People-Things and Data-Ideas dimensions underlying the RIASEC interest circumplex. Additionally, this study highlights the association between occupational group and Work Satisfaction ratings. However, individual differences and their fit with those environments did add predictive power above and beyond occupational membership alone. Future research should measure individual differences longitudinally along with outcomes and try to incorporate values measures as well to gain a more temporally sensitive and complete predictive model.

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