THE ROLE OF DISTINCTIVENESS IN ASSESSING VOCATIONAL PERSONALITY TYPES

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by

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The purpose of this study was to examine the distinctiveness of interest inventory scores. The researcher studied the difference between scores on the Self-Directed Search (SDS) in an effort to determine when a difference between two scores represents a significant and meaningful difference. Researchers commonly use the standard error of measurement (SEM) to determine confidence intervals for individuals’ true scores. The SEM for the SDS equals eight points, which means two scores must be separated by at least eight points to be considered distinct. Over time the SEM has become known as the “rule of eight”, and practitioners use it as a guideline for interpreting SDS results. However, researchers determined the SEM from a statistical formula, and no study has empirically examined this guideline. This study examined the distinctiveness of interest inventory scores by calculating the difference between individuals’ highest two SDS scores, while comparing congruence between two concurrent measures of vocational interest, both taken from the SDS.

SDS data was collected for 2397, (1497 female and 900 male), undergraduate students enrolled in the exploratory major at a large Midwestern university between 1996 and 2002. Primary-code distinction represented the absolute difference between the top two SDS scores. Expressed vocational interest and inventoried interest were compared to determine whether or not a congruent match existed between the two. Congruence results
were grouped by level of primary-code distinction in an effort to determine when
distinction scores represent a meaningful difference.

Descriptive statistics suggest a positive relationship exists between primary-code
distinction and congruence. Furthermore, distinction scores of four points appear to
distinguish between individuals top’ two SDS scores. Logistic regression confirmed the
existence of a significant positive relationship between primary-code distinction and
congruence, such that a one-point increase in primary-code distinction increases the
likelihood of finding congruence between expressed and inventoried interests by 8%.
Using these results, the researcher concluded that the “rule of eight” should be replaced
with the “guideline of four”, and that test manuals and interpretative routines for
practitioners be updated to reflect this distinction.
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I dedicate this work to my parents, Mary and Kevin Glavin Snr. Their acts of kindness, integrity, and generosity have shaped me into the person that I am today. The teachings that I provide my students, and the gift of counseling that I give my clients, extend directly from them. I love you both so dearly, and will be forever thankful for all that you have given me. I also feel indebted to the mentorship provided to me by my advisor, and friend, Dr. Mark Savickas. Thank you for your constant support and guidance.

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CHAPTER I

As the counseling profession moves toward evidenced-based interventions, researchers and practitioners are tasked with turning science into practice. Manualized interventions must be empirically validated before being used to provide mental health care. The counseling profession commonly calls upon practitioners to provide career interventions. Career practitioners often use the Self-Directed Search (SDS: Holland, 1994), one of the most widely used career interventions, to assist their clients. Holland (1997) originally designed the SDS as an intervention that could be self-administered. However, career practitioners are often recruited to help individuals interpret SDS results. Researchers, such as Holland and Rayman (1998) have developed guidelines to help interpret results. They developed these guidelines through empirical research. One of the most important guidelines refers to the “rule of eight”, which represents the standard error of measurement (SEM) for the SDS. Unfortunately, this guideline has never been empirically tested. Therefore, this study used empirical research to examine the “rule of eight”, with the intent of improving interpretative procedures for the SDS. The rest of this chapter discusses the move toward evidence-based practice, and describes how vocational guidance has applied the scientific method to provide quality career counseling interventions. The researcher describes the theory upon which Holland created one of the most popular career interventions currently available, the SDS, and discusses guidelines for interpreting results. The guideline known as the “rule of eight” is
explained, as well as the process through which Holland derived this guideline. The researcher then presents hypotheses designed to test the “rule of eight”.

In today’s age of accountability, mental health counseling attracts increased scrutiny. Responsible counselors can demonstrate accountability by using empirically validated practices. We see evidence of this growing movement in a task force created in 2005 by the American Psychological Association (APA). Appropriately named, the APA Presidential Task Force on Evidence-Based Practice (EBPP), the group promotes the use of empirically supported assessments and interventions aimed at providing the public with quality mental health care (APA, 2006). The task force defines EBPP as “the integration of the best available research with clinical expertise in the context of patient characteristics, culture, and preferences” (p. 273). This statement reflects the growing move toward integrating science and practice, a move that has important implications for the counseling profession.

Vocational Guidance and the Scientific Method

Vocational guidance, the precursor to mental health counseling, demonstrates a long and rich history of applying the scientific method. Walsh and Savickas (2005) detail the historical development of vocational psychology. The authors begin their review by covering vocational guidance between 1850 and 1908, a time when cities experienced rapid growth. This growth, driven by the industrial revolution, prompted a transition from agricultural to manufacturing, and resulted in families migrating from farms to cities. Spurred on by technological advances, factories, using complex machinery, began mass
developing goods. Scientific management, the brainchild of Frederick Winslow Taylor (1998), helped workers tend to these machines and maximize production. Highly detailed routines simplified assembly processes, and minimized production time. Taylorism proved profitable, but workers essentially became a part of the machine, employed to perform a series of specific tasks. The success experienced in specializing groups of tasks in one industry quickly led other industries to adopt similar production processes. This step would prove to be a significant one as specialized groups of tasks became known as jobs. Occupations followed as groups of jobs became categorized and differentiated.

As new industries created jobs and occupations, workers faced the challenge of choosing between the work available. On the farm, the need for choice did not exist, all work simply had to be completed. Faced with choice, and the freedom to choose, city workers required guidance. This guidance initially came from the Young Men’s Christian Association (YMCA), which helped in the placement of workers. As the need for assistance grew, Frank Parsons, considered to be the founder of vocational guidance, developed a method to help individuals choose fitting work. Parson’s method, detailed in his book “Choosing a Vocation” (1909), suggested that individuals should follow three steps in choosing an occupation: 1) know thyself, 2) know the factors required to be successful in a given line of work, and 3) use “true reasoning” to match oneself to an appropriate type of work. A century later, vocational guidance continues to use the concepts outlined in Parson’s matching approach. It reached its zenith in the person-
environment fit model, which Holland (1997) describes in his theory of vocational personality types and work environments.

Holland’s Theory

Holland’s theory rests upon seven assumptions. These assumptions describe Holland’s theory of vocational personality types and work environments, and explain how individuals make vocational choices. Holland details a total of seven assumptions: 1) Individuals can be categorized based on their resemblance to one of six personality types: Realistic, Investigative, Artistic, Social, Enterprising, and Conventional. These types are organized into what is known as the RIASEC hexagon. 2) Work environments can be categorized using the same RIASEC typology. 3) Individuals seek work that allows them to engage their personal skills, interests and values. 4) Vocational behavior can be understood by examining how individuals interact with work environments. 5) Individuals whose personality type matches their work environment type are considered to be congruent. 6) Individuals’ three letter SDS summary codes can be described in terms of consistency. Different degrees of consistency exist. The closer types are to one another on the RIASEC hexagon, the greater their consistency. 7) Individuals’ summary codes can be described in terms of differentiation. High levels of differentiation indicate individuals with well defined interests. Low levels of differentiation indicate individuals with diverse, and undifferentiated interests. The seven assumptions mentioned herein comprise the foundation of Holland’s theory, and the development of the SDS. A more
thorough analysis follows, and explains the details of these assumptions, and how they shape interpretative procedures.

**RIASEC Types**

Holland (1997) uses a hexagon to portray his model of personality types and work environments. Figure 1 illustrates Holland’s hexagonal model of personality types. The model categorizes individuals, and work environments based on their resemblance to six types: Realistic, Investigative, Artistic, Social, Enterprising, and Conventional. Realistic types prefer working with things, rather than people. They possess strong mechanical abilities, demonstrate solid manual and physical skills, and enjoy outdoor activities. Realistic type workers occupy positions such as mechanic, farmer, and electrician. Investigative types prefer to work with ideas. They possess strong math abilities, demonstrate solid scientific skills, and enjoy activities that involve in-depth thought. Investigative type workers occupy positions such as biologist, doctor, and researcher. Artistic types prefer working with feelings. They possess strong creative abilities, enjoy activities that involve imagination, and demonstrate skills in self expression. Artistic type workers occupy positions such as actor, writer and musician. Social types prefer to work with people, rather than things. They possess strong interpersonal abilities, demonstrate solid skills in empathic understanding, and enjoy activities that involve close personal contact. Social type workers occupy positions such as counselor, teacher and speech therapist. Enterprising types prefer working with opinions, rather than data. They possess strong leadership abilities, demonstrate solid skills in presenting, and enjoy persuading
others. Enterprising type workers occupy positions such as salesperson, business executive, and politician. Conventional types prefer working with data, rather than people. They possess strong numerical abilities, demonstrate solid organizing skills, and enjoy activities that involve planning. Conventional type workers occupy such positions as accountant, tax-preparer, and administrative assistant.

Just as individuals can be classified with a vector of resemblance to RIASEC types, work environments can be classified using the same typology. The majority of RIASEC types found within a particular work environment dictate the type of environment. For example, a research intensive university most resembles an Investigative environment, whereas a counseling center most resembles a Social environment. Holland’s (1997) theory suggests that individuals will be most satisfied if they work in an environment that fits their personality type. For example, Social individuals will be most content working in a counseling center, as opposed to a car repair shop. Holland developed a diagram of the RIASEC types, and arranged them as nodes on a hexagon, such that types closer together indicate a greater degree of similarity to one another.
Figure 1. Holland’s RIASEC Hexagon.
Although individuals demonstrate a resemblance to each of the RIASEC types, they do so to a greater or lesser degree, and tend to resemble one type more than another. When individuals complete the SDS they receive a score for each of the RIASEC types. Holland (1997) refers to these six scores as the SDS summary scores. The top three scores reflect individuals’ SDS summary code. The primary or dominant RIASEC type refers to the type for which individuals display the greatest amount of resemblance. SDS inventory results, as well as expressed vocational interests determine individuals’ primary RIASEC type. Data from the SDS technical manual (Holland et al., 1997) provide summary scale inter-correlations, for high school, college, and adult samples. These inter-correlations support the construct validity of the hexagonal model. The magnitude and direction of the relations closely resemble the proposed hexagonal structure of personality types proposed by Holland (1997). A meta-analysis, conducted, by Tracey and Rounds (1993) also found support for the arrangement of the RIASEC types.

*The Assumption of Congruence*

Assumptions three and four in Holland’s (1997) theory suggest that people tend to seek work that allows them to engage their skills, interests and values. Subsequently, understanding vocational behavior requires that one examine how individuals use their personalities to interact with occupations. According to Holland, a fitting vocational choice involves a matching process, where individuals choose work environments that match their personality type. Holland considers individuals whose personality type matches their work environment type to be congruent, assumption five. Numerous
indices exist to measure congruence. They range from the simple to the complex. A simple method for measuring congruence compares individuals’ primary SDS type to the primary type associated with their occupational or educational environment. A more complex method uses individuals’ top SDS three letters, along with a mathematical formula, to determine the degree of congruence. Among other things, researchers use the assumption of congruence to validate Holland’s theory. Career practitioners use the assumption of congruence to match individuals to fitting occupations. The current study uses the term congruence to define a match between individuals’ expressed vocational interests and their inventoried interests.

With so much research on congruence, meta-analytic writings best serve to describe the support for this construct. These writings combine the results of many studies on congruence that address the same, or similar, hypotheses. What follows, summarizes the findings of three such meta-analyses. Spokane, Meir, and Catalano (2000) conducted a meta-analysis of 66 published studies on congruence between 1985 and 1999, and reported positive, but weaker than expected, findings. The authors attributed this, in part, to the use of inappropriate research designs. Over time, however, studies have improved through the use of more sophisticated methodologies. For example, gathering data from working adults as opposed to readily available college students. Furthermore, advanced mathematical formulas have been developed and used to provide more accurate measures of congruence. The authors suggest a move from correlational studies to more robust studies, such as those based on experimental, quasi-
experimental, and longitudinal designs. In doing so, complex issues, such as studying the difference between the pattern of individuals’ interests and the degree of interest, may be resolved. With no research addressing such issues, the current study, which seeks to analyze a measure of congruence, while also examining the degree of difference between individuals’ first and second RIASEC types, may be the first of its kind. Spokane et al. underline the importance of this type of study because it provides a method by which to determine the RIASEC type in an SDS profile.

Given the diverse array of design methods used in past studies of congruence, Spokane et al. (2000) made the decision to include only those studies that exhibited strong internal and external validity. The studies deemed to meet the benchmark criteria for quality research displayed similar characteristics, which Spokane et al. used as grouping variables. This resulted in studies being organized into one of six groups. The first group contained experimental studies, and included research that analyzed career interventions, as well as ways in which individuals interact with their environment. The second group contained longitudinal studies. The third group contained correlational studies. The fourth group contained studies that involved measuring more than one dimension of congruence. The fifth group contained studies designed to test the effects of congruence when combined with moderator variables. The sixth group contained qualitative studies. Research findings based on the studies within these groups suggested significant relations exist between congruence and variables such as individuals’ perceived congruence, well being, job satisfaction, supervisor evaluations, job persistence
and stability, productivity, and quality of work. These results are consistent with outcomes hypothesized by Holland’s (1997) theory.

Since Holland introduced the concept of congruence in 1957, reported correlations between congruence and outcome variables have varied somewhat, Spokane et al. (2000). In a meta-analysis conducted by Assouline and Meir (1987), the authors reported 77 correlations from 41 studies where the correlation between congruence and job satisfaction ranged from -.09 to .51. However, upon grouping the correlations on two variables: 1) method used to type work environments, and 2) method used to measure congruence, the authors were able to explain the variance in the results, and provide more reliable estimates. Using these grouping variables, the authors found evidence to support correlations between congruence and job satisfaction greater than .30. This figure appears to agree with results from the studies conducted between 1985 and 1999 (Spokane et al., 2000), where the correlation between congruence and satisfaction approximated .25. Studies prior to 1985 also suggest a relation of similar magnitude between congruence and satisfaction, (Spokane, 1985). In analyzing 63 studies on congruence, Spokane found correlations between congruence and performance, satisfaction, and stability, with results ranging from .25 to .35. Furthermore, Spokane found evidence to suggest that differentiation and consistency moderate the effects of congruence.

*The Construct of Consistency*

The assumption of consistency describes the degree of similarity among personality types. Holland (1997) operationally defines consistency as the proximity of
the first two letters in the RIASEC profile. Consistency provides a measure of the stability of individuals’ vocational identity. Holland suggests that individuals with stable identities possess a clearer picture of their vocational self-concept and goals, and tend to be more predictable than those with unstable identities. Consistency makes it easier for individuals to locate congruent work environments because they possess focused, rather than diverse, interests.

Calculating the different degrees of consistency involves using the RIASEC hexagon to map the distance between the first two letters in the RIASEC profile. Adjacent letters on the hexagon indicate a high degree of consistency. Figure 2 shows an example of a highly consistent profile, where the first two RIASEC letters equal AS. Letters separated by one node on the hexagon indicate a moderate degree of consistency. An example of a moderately consistent profile would be a code that begins with AE. Letters directly opposite one another on the hexagon indicate a low degree of consistency. An example of an inconsistent profile would be a code that begins with AC.
Figure 2. RIASEC Hexagons Showing Examples of High, Medium, and Low Consistency.
Despite a sound theoretical argument, the assumption of consistency has received mixed support from the literature. Given Holland’s (1997) argument that consistent individuals exhibit a clearer and more stable sense of identity than inconsistent individuals, one would expect such individuals to also exhibit greater levels of congruence, job satisfaction, persistence, and predictability. While some research confirms these hypotheses, other results seem inconclusive. Aiken and Johnston (1973) studied the vocational behavior of a sample of undecided college students, and found students with consistent profiles participated more in gathering information on occupations than did students with inconsistent profiles. Barak and Rabbi (1982) studied the consistency of college major for a sample of students, and found consistent students exhibited higher achievement, fewer changes in major, and greater persistence in college, than inconsistent students. O’Neil and Magoon (1977) studied the predictability of Investigative personality types at different levels of consistency. They found individuals with higher degrees of consistency to be more predictable, four years later, with regard to their final major choice, as well as their current and future vocational intentions. Another study by O’Neil, Magoon, and Tracey (1978) followed up with these students three years after they graduated. Results suggested degree of consistency relates positively to prediction of vocational choice for Investigative type males. Wiley and Magoon (1982) found a relation between degree of consistency and persistence in college for a sample of freshman students identified as Social types, with a 59% graduation rate for highly consistent individuals and a 36% graduation rate for individuals who demonstrated less
consistent profiles. Furthermore, individuals with higher levels of consistency demonstrated significantly higher GPA results than individuals with lower levels of consistency.

Other studies have failed to support the assumption of consistency. A study of college freshman conducted by Erwin (1982) found no relation between consistency and students’ number of major changes, course withdrawals and academic achievement. Latona (1989) found no relation between consistency of interest profiles and persistence in college for a sample of college students. Reuterfors, Schneider and Overton (1979) found conflicting results for a sample of college freshman, where academic achievement decreased between highly consistent and moderately consistent students, but then increased for students who exhibited the lowest degree of consistency. Similarly, O’Neil (1977) found no relation between consistency and GPA for a sample of male investigative college students. The literature provides evidence of mixed results for the assumption of consistency. Despite the mixed results, consistency remains a factor worthy of further research.

*The Construct of Differentiation*

Differentiation describes the degree to which individuals resemble one personality type over another. Well differentiated profiles exhibit peaks and valleys, as a result of high and low scores. Undifferentiated profiles appear flat as a result of similar scores. Holland (1997) believes individuals who demonstrate high levels of differentiation possess well-defined interests, abilities, and skills, which make them more predictable.
Individuals who demonstrate low degrees of differentiation possess broad interests, abilities and skills, which them less predictable. Differentiation plays an important role in the current study because this research examines the degree of congruence between expressed vocational interests and inventoried interests, at different levels of differentiation between individuals’ top two RIASEC types. Researchers have created numerous indices for calculating differentiation. The original, and simplest method, involves obtaining the absolute numerical difference between the highest and lowest values in the six SDS summary scores. Similar to the research on congruence, researchers have spent a significant amount of time and effort studying differentiation.

In reviewing a number of studies on differentiation between 1960 and 1996, Holland (1997) concluded that support existed for differentiation, although this support appeared to be weaker than what he expected. He attributed this, in part, to research design issues, suggesting that strong designs provided support for differentiation, whereas weak designs provided less support. Strong designs included those studies that used large diverse samples of participants, a fitting research design, and standard outcome measures. Weak designs included those studies that used small homogenous samples of participants, poor research designs, and questionable instruments. Overall, Holland concluded that, when researchers employ strong research methodology, studies provide support for the assumption of differentiation. Supporting research suggests differentiation is related positively to job satisfaction (Wiggins, Lederer, Salkowe, & Rys, 1983), occupational choice satisfaction in men (Peiser & Meir, 1978), the stability of vocational choice
(Holland, Gottfredson, & Baker, 1990), student development (Erwin, 1987), academic achievement (Swanson & Hansen, 1986; Frantz & Walsh, 1972), and decision making (Holland, Gottfredson, & Nafziger, 1975).

The Construct of Profile Elevation

Although not included as an assumption in Holland’s (1997) theory of vocational choice and personality types, some researchers have suggested the elevation of a RIASEC profile may hold important information for interpreting SDS results. Profile elevation refers to the total sum, or mean, of RIASEC scores in a profile. The total can range from 14 to 300. Individuals with highly elevated profiles tend to be more social, optimistic and active in seeking out new experiences, than those with low elevation profiles (Bullock & Reardon, 2005). Profile elevation aids career practitioners in interpreting SDS results. For example, career practitioners may use the construct of profile elevation in conjunction with Holland’s (1997) assumption of differentiation to interpret undifferentiated profiles. Take for example the following two RIASEC profiles, R=13, I=12, A=11, S=11, E=9, C=9, and R=43, I=42, A=41, S=41, E=39, C=39. The differentiation for both profiles equals four points. However, profile elevation for the first individual equals 65, with a mean of 10.8, while the profile elevation for the second individual equals 245, with a mean of 40.8.
Figure 3 illustrates the difference between the two profiles. Clearly, one should not interpret these profiles in a similar manner. Although both profiles appear to be undifferentiated, a career practitioner interpreting Profile B might see an individual with an energetic personality, who makes impulsive decisions, and has difficulty distinguishing between interests. Alternatively, a career practitioner interpreting Profile A might see an individual with a lack of interests, and someone who has not explored the world of work.
Figure 3. Examining Profile Elevation for Profiles with Equal Differentiation Scores.
Few empirical studies have examined profile elevation. Therefore, some doubts remain in determining what constitutes high and low elevation. Bullock and Reardon (2005) used norms from the *Self-Directed Search Technical Manual* (Holland et al., 1997) to calculate low, average, and high elevations. The authors calculated the following ranges of profile elevation using an individuals’ total SDS scores; Low elevation = scores less than 128 for men, and 127 for women, Average elevation = scores between 129 and 149 for men, and between 128 and 146 for women, High elevation = greater than 150 for men, and 147 for women. Despite performing these calculations, Bullock and Reardon suggest future studies use local norms to calculate levels of profile elevation.

The lack of studies on profile elevation highlights the limited research on this topic. However, results from studies that have been conducted suggest the topic warrants further research. Swanson and Hansen (1986) examined profile elevation scores for a sample of undifferentiated college students. Separating the students into two groups, high-score undifferentiated (HSU) and low-score undifferentiated (LSU), the researchers examined the differences between students with high and low profile elevations. Results suggested HSU students demonstrated higher average cumulative GPA and academic comfort scores. In addition, results suggested HSU students were more likely to persist in college. The current study considers the effect of profile elevation on the degree of congruence between expressed vocational interests and inventoried interests for the SDS at varying levels of differentiation. The results will help determine the moderating
influence of profile elevation on congruence, and provide practitioners with enhanced interpretative guidelines for the SDS.

Moderator Variables

Moderator variables affect the strength and direction of the relation between two other variables. This means that the relation between two variables, such as a predictor and criterion variable, changes when we introduce a third variable. Introducing the third variable allows the variance between the predictor and criterion variable to be partitioned. The partitions improve the ability of the predictor variable to predict the criterion variable. Holland (1997) suggests that the variables of consistency and differentiation, moderate the relation between the predictor variable, congruence, and criterion variables such as job satisfaction, productivity, and quality of work. Frantz and Walsh (1972) studied the additive effects of consistency, differentiation, and congruence on academic achievement and satisfaction for a sample of graduate students. They found graduate students characterized as consistent, differentiated, and congruent demonstrated the greatest academic ability, and satisfaction. Henner and Meir (1981) found similar results, reporting an additive effect for consistency, differentiation, and congruence on job satisfaction in a sample of clinical nurses. Villwock, Schnitzen, and Carbonari (1976) examined congruence, differentiation, and consistency as predictors of vocational choice and stability for a sample of undergraduate college students. The authors examined the predictors individually and in combination with one another. They found no evidence to suggest either differentiation, or consistency, moderate the effect of congruence on
vocational choice and stability. However, when studied individually, results indicated the relative predictive ability of each, with the following order of importance observed: 1) congruence, 2) differentiation, and 3) consistency.

The current study examined congruence between expressed vocational interests and inventoried interests, while considering the numerical difference between participants’ first and second SDS scores. The researcher refers to the difference between participants’ first and second SDS scores as primary-code distinction. Theoretically, the relation between congruence and primary-code distinction will be moderated by consistency and differentiation. For example, the overall relation between congruence and primary-code distinction may appear to be positive, but weak. However, when we add the moderating variable, consistency, to the model, the relation between congruence and primary-code distinction may change such that it becomes positive, and strong. The relation between congruence and primary-code distinction may be high for participants who demonstrate highly consistent profiles, but low for participants who demonstrate inconsistent profiles. Figure 4 provides a theoretical example of the moderating effects of consistency on the relation between congruence and primary-code distinction. While there appears to be no relation between congruence and primary-code distinction for participants with inconsistent profiles, there does appear to be a strong positive relation between congruence and primary-code distinction for participants with highly consistent profiles.
Figure 4. Example of the Moderating Effects of Consistency on the Relation Between Congruence and Primary-Code Distinction.
The Self-Directed Search

The Self-Directed Search operationally applies Holland’s theory of vocational personality types and work environments. The instrument gathers information on vocational interests, both expressed and inventoried. Considered a vocational intervention, the SDS encourages individuals to use their results to explore occupations for which they appear best suited. Although test companies do not release official usage figures, the SDS is widely accepted as one of the most popular instruments used for career guidance and counseling throughout the world. The publisher, Psychological Assessment Resources Inc. (PAR), claims the SDS has served over 22 million people, and has been translated into 25 different languages. The instrument has gone through a number of revisions (1977, 1984, 1994) since being introduced in 1970. With the popularity of the internet, PAR created an online version of the SDS, which can be found at http://www.self-directedsearch.com.

The SDS deserves its popularity and owes its success, in part, to a clear conceptual model. The model describes the world of work in a manner that makes it easy for both career practitioners and clients to understand and apply. Holland’s (1997) theory suggests individuals differ based on their interests, and can be categorized as resembling one of six personality types: Realistic, Investigative, Artistic, Social, Enterprising, and Conventional. Holland refers to these types as the RIASEC types. The theory suggests that work environments can be categorized using the same RIASEC typology. Making a vocational choice then becomes an exercise in matching individuals to the most
appropriate work environment. The SDS not only provides users with a list of compatible occupations to explore further, it also communicates information about how we structure and organize the world of work. Individuals can use this information to make informed decisions about work environments, and where they best fit. The clear and concise nature of Holland’s theory, combined with an easy to use, self-administered instrument, has made the SDS a popular career tool in career guidance and counseling.

Practitioners find the ease by which Holland’s (1997) theory can be understood complemented, and supported, by a rich body of research. In particular, a significant amount of research exists to support the validity and reliability of the SDS. Details of the psychometric properties of the instrument can be found in the SDS Professional User’s Guide, (Holland, Powell, & Fritzsche, 1997), and the SDS Technical Manual (Holland, Fritzsche & Powell, 1997). These resources describe the theoretical concepts Holland used to create the SDS, and provide a number of guidelines that practitioners can use to interpret SDS profiles. One such guideline refers to the “rule of eight”, which Holland derived from a statistical measure known as the Standard Error of Measurement (SEM). Despite the extensive research conducted on the SDS, no study has examined the “rule of eight”. Without empirical evidence, the “rule of eight” may well be the ‘rule of 4’, or possibly the “rule of 12”. The current study examined the “rule of eight” in an effort to improve interpretative guidelines for the SDS. The SDS interpretative guidelines will be reviewed, and hypotheses presented, to help improve current interpretative procedures.
The Rule of Eight

The rule of eight aids practitioners and researchers in interpreting RIASEC profiles, and helps to determine an individual’s dominant personality type. This rule suggests that the numerical difference between two RIASEC types must be at least eight points for the difference to be considered meaningful. Holland (1997) derived this interpretative guideline by calculating the standard error of measurement (SEM) for the SDS. The SEM can be calculated using the formula; \( s\sqrt{1 - r} \), where \( s \) equals the standard deviation for the instrument, and \( r \) equals the reliability coefficient. In the context of this research, the researcher used congruence to operationalize the study, and test the hypotheses. Participants demonstrated congruence if there existed a match between their expressed vocational interest and their inventoried interest. RIASEC results that demonstrate primary-code distinction scores less than eight points are considered indistinct, and decrease the probability of congruence. This is because participants, whose top two RIASEC scores are indistinct, are just as likely to find their expressed vocational interest type match either the first, or second, letter in their RIASEC code. Participants whose top two RIASEC scores are distinct are more likely to see their highest RIASEC score match, or be congruent with, their expressed vocational interest type. Therefore, this study examines primary-code distinction scores to see if people with distinctive scores talk differently about their expressed vocational interest when compared to people with indistinctive scores.
Psychometricians consider the SEM an important property for instruments like the SDS because it provides a measure of the instrument’s reliability. Reliability refers to an instrument’s ability to return accurate and consistent results. For example, if individuals complete the SDS on two different occasions, they should receive the same, or at least similar, results. When individuals complete the SDS they calculate their own scores for each of the RIASEC types. If a group of individuals took the SDS repeatedly, they would sometimes exhibit higher scores, and sometimes exhibit lower scores. Psychometricians refer to these scores as observed scores. Individuals’ observed scores represent only an estimate of their true score. This is because the estimate includes some amount of error, which must be calculated and reported to practitioners to help them interpret SDS profiles. The SEM, which Holland calculated to be eight points, provides an estimate of this error.

In practical terms, the SEM helps to determine when a difference in scores between RIASEC types represents a meaningful difference. Differences less than eight points between two types do not reflect meaningful differences because they fall within the SEM. Ultimately, the SEM helps to establish the order of the RIASEC types within individuals’ SDS profiles. For example, if an individual receives the following SDS results, R=20, I=18, A=16, S=15, E=14, C=13, one might conclude the top three letters of this profile to be RIA. However, since the difference in scores between any two of these types falls within the SEM, i.e. eight points, the actual order has an equal probability of being any permutation of the letters R, I, and A. This example shows that
the “rule of eight” has important implications for practitioners who interpret SDS profiles. However, despite being used to interpret SDS profiles, researchers have never empirically tested the “rule of eight”, and this indicates a gap in the literature. This study examines the rule of eight, and attempts to identify when differences between individuals’ first and second RIASEC types represent meaningful differences. This research has practical implications for career counseling because it will improve the guidelines that counselors use to interpret SDS results.

Figure 5 displays an example of two indistinct, and indistinguishable, RIASEC scores, where Realistic = 30 and Investigative = 26. To calculate the upper confidence interval for Realistic we add the SEM to the observed score, i.e. 30+4 = 34. To calculate the lower confidence interval for Realistic we subtract the SEM from the observed score, i.e. 30-4 = 26. The difference between the upper and lower bounds represents eight points, which equals the SEM. Using these confidence intervals, and the properties of the normal curve, we can say that 68 times out of 100, the true score for an observed score of 30 will fall between 26 and 34. To calculate the upper confidence interval for Investigative we add the SEM to the observed score, i.e. 26+4 = 30. To calculate the lower confidence interval for Investigative we subtract the SEM from the observed score, i.e. 26-4 = 22. Using these confidence intervals we can say that 68 times out of 100, the true score for an observed score of 26 will fall between 22 and 30. The shaded area represents the amount of overlap between the confidence intervals for the Realistic and Investigative scores, and provides an example of how to interpret the “rule of eight”.
When the confidence intervals overlap, one cannot determine the true order of the two types, because the difference between their observed scores falls within the SEM. Therefore, the “rule of eight” provides practitioners with a guideline for interpreting results when two scores are statistically indistinguishable. In this example, where the difference between the top two scores, Realistic and Investigative, equals four points, practitioners would advise the individual to consider equally both RI and IR occupations.
Figure 5. An Example of Two Indistinct RIASEC Scores Using the “rule of eight”.

Figure 5.
Figure 6 displays an example of two distinct, and distinguishable, RIASEC scores, where Realistic = 32, and Investigative = 24. The dotted lines represent the confidence intervals for both scores. To calculate the upper confidence interval for Realistic we add the SEM to the observed score, i.e. $32 + 4 = 36$. To calculate the lower confidence interval for Realistic we subtract the SEM from the observed score, i.e. $32 - 4 = 28$. Using these confidence intervals we can say that 68 times out of 100, the true score for an observed score of 32 falls between 28 and 36. To calculate the upper confidence interval for Investigative we add the SEM to the observed score, i.e. $24 + 4 = 28$. To calculate the lower confidence interval for Investigative we subtract the SEM from the observed score, i.e. $24 - 4 = 20$. Using these confidence intervals we can say that 68 times out of 100, the true score for an observed score of 24 will fall between 20 and 28. This example illustrates the “rule of eight”, which suggests that for two scores to be considered truly different, they must be separated by at least eight points. When the scores differ by eight points, such as the scores in this example, the confidence intervals do not overlap. Therefore, we can be confident that the two types are in fact distinct, and that the two letter type, RI, reflects the correct order.
Figure 6. An Example of Two Distinct RIASEC Scores Using the “rule of eight”.
Excluding the original normative data, which Holland used to test the psychometric properties of the SDS, the “rule of eight” has never been empirically tested. Therefore, the “rule of eight” may actually be the ‘rule of four’, or the ‘rule of fourteen’. The lack of research on this topic represents a gap in an extensive body of literature for the SDS. This study tested the rule of eight by comparing participants’ primary expressed vocational interest to their primary inventoried interest. The researcher organized results by using primary-code distinction scores as a grouping variable. This allowed the researcher to see how the degree of distinctiveness between participants’ top two SDS scores affected congruence between participants’ expressed and inventoried interests.

Measuring Interests

Four primary assessment methods exist to assess interests: 1) Inventoried interests, 2) Tested interests, 3) Expressed interests, and 4) Manifested interests (Super, 1947). Inventories assess interests by tallying responses to lists of activities and occupations. Responses suggest a preference for some interests over others. Tests assess interests by measuring responses to items, based on occupations, for which there exist right and wrong answers. The logic behind this method suggests that individuals know more about those occupations for which they have the greatest interest. Expressions assess interests based on individuals’ written, and oral, preferences for certain activities or occupations. Manifest behaviors assess interests based on the activities in which individuals choose to engage. Observable and measurable, manifested interests provide a way to measure interests by identifying what, and how much, individuals participate in an
activity. The order of these methods for assessing interests indicates their degree of validity and accuracy. Inventoried interests represent the least accurate method for identifying interests, while manifested interests represent the most accurate method for identifying interests. Inventoried interests require that individuals choose their responses from fixed lists of options. Individuals do not have the opportunity to express interests outside of the lists presented. Tested interests provide a greater degree of accuracy based on the premise that individuals possess more knowledge about the type of occupational fields for which they have an interest. Expressed interests provide an even greater degree of accuracy because individuals’ responses reflect what they intend to do. Individuals’ intentions describe their objective goals, and make engagement in expressed interests more likely. Furthermore, freedom to express choice allows individuals to communicate more specific, and accurate, interests. Manifested interests provide the greatest degree of accuracy because they represent the actual activities in which individuals engage. Although manifested interests provide the best method for assessing individuals’ interests, such research requires the analysis of longitudinal data, which the current dataset did not include. However, data for expressed interests, the next best alternative, does exist in the dataset, available in the form of individuals’ responses to the occupational daydreams section of the SDS.

Expressed Interests

Researchers and practitioners often use a variety of open-ended questions to gather information on expressed vocational interests. Varying the terminology used to ask
these questions results in different responses. Trow’s (1941) Vocational Choice Inventory (VCI) explains these differences, and lists three types of open-ended questions, each of which represent a different method for assessing expressed vocational interests. Question one requests that individuals state their probable occupation upon leaving school, which Trow suggests assesses vocational choice. Question two requests that individuals state their possible occupation, assuming that they receive the necessary training or education, which Trow suggests assesses vocational preference. Question three requests that individuals state their fantasy occupation, where they identify an occupation they would like to enter, regardless of how realistic their selection may be. Trow suggests this fantasy question assesses an individual’s vocational aspiration. Although similar, each questions prompts individuals to express their vocational interests using varying degrees of realism.

Researchers and practitioners should understand the degree of realism required to answer questions on vocational interests. Crites (1969) explains the importance of semantics when considering terms related to expressions of vocational interest. Vocational choice indicates individuals’ intent, and takes into account numerous factors that might affect their level of occupational satisfaction. As such, Crites considers vocational choice to be the most realistic statement of occupational choice. Vocational preference indicates what individuals would like to do if given the choice between two or more occupations, and the freedom to choose between them. Therefore, vocational preference allows individuals to be somewhat less realistic about their occupational choice. Vocational aspirations indicate individuals’ ideal occupations, and represent what
they wish to do. These responses require less realism, because individuals do not have to consider factors that might constrain their choices. However, individuals benefit by experiencing greater freedom to express their interests.

The first section of the SDS asks individuals to express their vocational interests by listing both their vocational daydreams as well as the occupations they have discussed with other people. The space provided allows individuals to list up to eight occupations in chronological order, starting with the most recent. The current study uses the data collected in section one of the SDS to represent individuals’ expressed vocational interests. Research suggests expressed interests demonstrate similar, and often better, predictive ability, than inventoried interests. Dolliver (1969) conducted a meta-analysis to compare the psychometric properties of inventoried interests and expressed interests. The Strong Vocational Interest Blank (SVIB) was used as the instrument to measure inventoried interests, while the measure used to elicit expressed interests varied. The SVIB exhibited superior reliability when compared to expressed interests. However, the predictive validity of expressed interests proved to be as good as, and more often, greater than that for inventoried interests. Dolliver concluded that inventoried interests, as measured by the SVIB, are no better at predicting future occupational choice, than expressed interests. Contrary to the evidence however, expressed interests receive less attention from researchers and practitioners, leading Dolliver to suggest that a prejudice exists against expressed interests. Since Dolliver’s meta-analysis, a number of other
studies have provided support for the use of expressed interests (Cairo, 1982; Bartling & Hood, 1981; O’Neil & Magoon, 1977; Gottfredson & Holland, 1975; Whitney, 1969). Like Dolliver (1969), Borgen and Seling (1978) used the SVIB to study the predictive validity of inventoried and expressed interests. They administered the SVIB to 1455 male high school students just prior to their entry into college. At the same time, students also provided expressed interests for a specific major and career. Students specified these interests from a list of 99 majors and 99 careers that the researchers provided. Three years later, students provided follow-up information on their chosen major and anticipated career choice. The results showed that expressed interests correctly predicted individuals’ major and career choices 52.4%, and 52.4% respectively. The SVIB predicted major and career choice 30.8%, and 40.2% respectively. This suggests expressed interests predict future major and career choice better than inventoried interests. Further analysis categorized the data into one of two groups, congruent and incongruent. The congruent group contained those students whose expressed and inventoried interests agreed. The incongruent group contained those students whose expressed and inventoried interests disagreed. As one might expect, the percentage of correct predictions for major and career choice increased for the congruent group, 71.3% and 70.0%, respectively. The percentage of correct predictions for major and career choice decreased for the incongruent group. Inventoried interests for incongruent students predicted future major and career choice 14.3%, and 22.5% of the time, respectively. Expressed choice for incongruent students predicted future major and career choice
45.0%, and 41.4% of the time, respectively. These results suggest that when inventoried results and expressed choices do not match, expressed choice remains a better predictor of future major and career choice.

Support for the use of expressed interests also comes from Holland, Gottfredson and Baker (1990), who conducted a study where they showed a single vocational aspiration, when classified by Holland type, equaled or exceeded the predictive validity of an interest profile, also classified by Holland type. The study consisted of 717 navy recruits, 467 men and 250 women. At the start of training, the researchers provided recruits with a list of 96 occupations. Recruits used these occupations to list their top three vocational aspirations, which researchers recorded as early choice one, early choice two, and early choice three. Recruits also completed the Vocational Preference Inventory (VPI). The VPI is an interest inventory composed entirely of occupational titles. It can be used to measure an individual’s dominant personality type, and utilizes Holland’s (1997) RIASEC typology. Upon completing training, the researchers provided recruits with the same list of 96 occupations. Recruits listed their top three vocational aspirations, which researchers recorded as late choice one, late choice two, and late choice three. Results showed that recruits’ first vocational aspiration, recorded prior to training, predicted their future vocational aspiration far better (75.5%), than the prediction made from the VPI, which only predicted an individual’s future vocational aspiration 36.3% of the time.

Similar to the current study, Touchton and Magoon (1977) researched expressed and inventoried interests using the SDS. The authors studied the predictive validity of the
SDS by comparing the effectiveness of the occupational daydreams section and the inventoried results section in predicting the vocational plans for a sample of college women. Upon matriculation, participants completed the SDS. Three years later, participants completed a questionnaire, listing their current major and the two most likely occupations they would enter. The most recent occupational daydream predicted academic major for 68% of the participants, while the SDS summary code predicted academic major for 61% of the participants. The most recent occupational daydream predicted the top occupational choice for 64% of the participants, while the SDS summary code predicted the top occupational choice for 56% of the participants. The authors also found that the degree of prediction increased when there was agreement between participants’ most recent occupational daydream and their SDS summary code. Like Touchton and Magoon, the current study examines the validity of the SDS. However, rather than research the predictive validity of the SDS, the current study examines concurrent validity by analyzing congruence between participants’ expressed vocational interest and their inventoried interest. Furthermore, the analysis examines congruence while also taking into account the numerical difference between participants’ top two RIASEC types, i.e. primary-code distinction. This will help the researcher identify the relative effect of primary-code distinction on congruence, while also determining how well the “rule of eight” identifies congruent and incongruent participants. This research helps to improve manualized treatment procedures for
individuals seeking career guidance. Furthermore, using empirical research to test the “rule of eight” follows the move toward evidence-based practice.

Hypotheses

H1: Congruence between RIASEC type and expressed vocational interest is greater for individuals whose degree of primary-code distinction is greater than, or equal to, eight points.

H2: Primary code distinction relates positively to congruence between RIASEC type and expressed vocational interest.

H3: Consistency moderates the relation between primary code distinction and congruence.

H4: Differentiation moderates the relation between primary code distinction and congruence.

H5: Profile elevation moderates the relation between primary code distinction and congruence.

Summary

As career practitioners strive to provide clients with quality guidance and counseling, and governing bodies seek to raise levels of accountability, there exists an increasing need to research and develop evidence based practices. The SDS is one of the most commonly used career instruments throughout the world. Built upon a solid theoretical framework, and demonstrating strong psychometric properties, the SDS provides career practitioners with a quality evidence based instrument. An extensive and
A rich body of research provides support for the SDS and Holland’s (1997) theory of vocational choices and personality types. The majority of this research tends to focus on the SDS and the constructs upon which the instrument depends, while fewer studies examine how to interpret SDS results. The current study attempted to improve interpretative guidelines for the SDS by examining the “rule of eight”. The “rule of eight” reflects the standard error of measurement for the SDS. However, this guideline remains unexamined and untested. The current study tested the “rule of eight”, while considering the moderating effects of variables such as differentiation, consistency and profile elevation. The researcher operationalized the study using congruence to determine if participants’ expressed vocational interests matched their inventoried interests. This enabled the researcher to see if the “rule of eight” helps to identify participants who express vocational interests that match their inventoried interests. Empirically researching the “rule of eight” helps to further develop interpretative guidelines for the SDS, and provide career practitioners with further evidence to support the use of this instrument.
CHAPTER II

METHODS

The current study investigated interpretative guidelines for the SDS. This chapter explains the methodology used to collect and study the data, and describes the participants, measures, procedures, and analyses. The participants section provides details about the individuals who participated in the study. The measures section operationally defines the variables stated in the hypotheses in chapter 1, and includes a discussion of RIASEC type, expressed vocational interest, congruence, differentiation, consistency, and profile elevation. The procedures section explains how the researcher gathered and coded the data. The analyses section explains how the researcher analyzed data.

Participants

The participants were 2397, (1497 female and 900 male), undergraduate students enrolled in the exploratory major at a large Midwestern university between 1996 and 2002. Students who choose to enroll in this major do so because they have not yet decided on an academic major. Coordinated through the department of Undergraduate Studies, these students receive assistance with degree and career planning. Advisors monitor students’ academic progress, and assist them in developing career goals. Students remain with the same academic advisor until they declare a degree-granting major. During this time, students engage in career exploration and planning in an attempt to identify their skills, interests, and abilities. Program coordinators believe the self-knowledge and information gathered from these activities assists students in choosing a
fitting major. Many freshman students choose the exploratory major as a starting point for their academic journey at this institution. However, students may only accrue 60 credit hours in this program before being expected to declare another major. All freshmen enrolled in the college of undergraduate studies as exploratory students attend a mandatory semester long orientation program aimed at enhancing their chances of academic success. The program requires that students complete the Self-Directed Search (SDS: Holland, 1994). Orientation instructors administer the SDS as a take home assignment during week five of a sixteen week semester.

Measures

RIASEC Type

Students’ RIASEC type was operationally defined as the highest raw score from their SDS results. Composed of two parts, the SDS can be self-administered and self-scored, and takes approximately 20 minutes to complete. Part one asks individuals to list their occupational daydreams in chronological order, starting with the most recent. The space provided allows individuals to list up to eight entries. Part two consists of 228 statements, organized into four sections: activities, competencies, occupations, and self-estimates. Section one prompts individuals to respond “like” or “dislike” to a list of 11 activities for each of the RIASEC types. Each “like” response receives one point, which results in scores ranging from 0 to 11 points for each of the RIASEC types. Section two prompts individuals to respond “yes” or “no” to a list of 11 personal competencies for each of the RIASEC types. Each “yes” response receives one point, which results in
scores ranging from 0 to 11 points for each of the RIASEC types. Section three prompts individuals to respond “yes” or “no” to indicate a like for, or dislike for, a list of 14 occupations for each of the RIASEC types. Each “yes” response receives one point, which results in scores ranging from 0 to 11 points for each of the RIASEC types. Section four contains two questions, which prompt individuals to rate their abilities based on each of the RIASEC types. A Likert scale records responses, with options ranging from 1 to 7, where 1 = low ability and 7 = high ability. Scores for section four range from 2 to 14 for each of the RIASEC types. Subsequent pages explain scoring procedures to help users determine their SDS profile. This involves summing the RIASEC scores in each of the four sections. Total scores for each of the RIASEC types range from 2 to 58. Organizing the highest three scores in descending order provides individuals with their three letter SDS summary code. The letter with the highest score indicates an individual’s primary SDS code, and thus RIASEC type. Upon completing the intervention, further directions prompt individuals to use the Occupations Finder (Holland, 2000) to locate occupations that match their SDS summary code.

The SDS Technical Manual (Holland, Fritsche & Powell, 1994) presents information regarding the psychometric properties of the SDS. The following provides a summary of this information. The normative sample consisted of 2,602 students and working adults, 1002 males and 1600 females. The six summary scales identify an individual’s personality type based on his or her resemblance to Holland’s (1997) RIASEC typology. Reliability estimates have been calculated for the summary scales, as
well as the sections that comprise each scale. Internal consistency reliability estimates for
the summary scales ranged from .90 to .94. Internal consistency reliability estimates for
the Activities, Competencies, and Occupations scales ranged from .72 to .92. Internal
consistency reliability estimates for the two measures of Self-Estimates ranged from .37
to .84. A study involving 73 participants provided evidence to support the test-retest
reliability of the SDS. During this study researchers tested and re-tested participants over
periods ranging from four to twelve weeks, and found test-retest correlations for the
summary scales ranging from .76 to .89. The authors report the standard error of
measurement (SEM) for the summary scales to be eight points. Therefore, numerical
differences of less than eight points between any two types do not represent meaningful
differences.

Construct validity has been established through reported inter-correlations
between the RIASEC summary scales, which approximate the hexagonal model proposed
by Holland (1997). Criterion-related validity has been demonstrated through concurrent
hit rates between SDS high-point codes, vocational aspirations, college major and
occupational attainment for samples of high school students, college students, and
working adults. Hit rates were calculated using the normative data collected in 1994. A
match between high school students’ high-point codes and their vocational aspirations
indicated a hit. A match between college students’ high-point codes and their vocational
aspirations, or college major, indicated a hit. A match between adults’ high-point codes
and their vocational aspirations, college majors, or current occupations indicated a hit.
Hit rates ranged from 35.5% to 60.1% with an average of 54.7%, thus providing evidence of concurrent validity. Research using previous editions of the SDS: 1985, 1977, 1971, and 1965, provides additional evidence to support the concurrent validity of the instrument. Concurrent hit rates from previous research range from 46.7% to 76%, suggesting average to high concurrent validity. Predictive hit rates, over a period of one to seven years, ranged from 39.6% to 79.3%, suggesting average to high predictive validity.

The *SDS Technical Manual* reports comparisons of the predictive ability of expressed vocational interests with inventoried results from several other interest inventories, which use scales that parallel the six RIASEC types. Expressed vocational interests, taken from the SDS, demonstrated greater predictive ability than inventoried results taken from several interest inventories including, the SDS (Holland, 1994), the Vocational Preference Inventory (VPI; Holland, 1965), the Strong Vocational Interest Blank (SVIB; Strong, 1965) and the Strong Campbell Interest Inventory (SCII; Campbell, 1977). Using the high-point code from individuals’ inventoried results yielded hit rates between 26.9% and 66.4%, with an average of 44.9%. Using the first letter of individuals’ expressed vocational choices yielded hit rates between 38.5% and 78.2%, with an average of 57.2%.

*Expressed Vocational Interest*

Part 1 of the SDS asks individuals to list their occupational daydreams. The researcher recorded written responses to the occupational daydreams section, and
assigned three letter SDS codes to each response using the Dictionary of Holland Occupational Codes (DHOC; Gottfredson & Holland, 1996). The DHOC acts as a reference guide, providing SDS codes for 12,860 occupations. When participants listed occupations that could not be located in the DHOC, two vocational counseling experts discussed and assigned the most appropriate three-letter SDS code. The first SDS letter of individuals’ most recent occupational daydreams was used to type their expressed vocational interest.

**Congruence**

Generally, studies of vocational congruence involve matching a predictor variable to a criterion variable. Holland’s (1997) congruence assumption measures the degree to which an individual’s personality type, the predictor variable, matches his or her work environment, the criterion variable. The current study defined congruence as an exact match between individuals’ RIASEC type and their expressed vocational interest. Expressed vocational interest represents the predictor variable. RIASEC type, which provides a measure of an individual’s inventoried interests, represents the criterion variable.

**Differentiation**

Differentiation reflects the degree to which individuals resemble one RIASEC type over others. Calculating differentiation involves subtracting the lowest RIASEC score from the highest RIASEC score. High levels of differentiation suggest individuals
have well-defined interests, whereas low levels of differentiation suggest individuals with diverse interests.

*Primary-Code Distinction*

Primary-code distinction measures the difference between individuals’ highest, and second highest, RIASEC scores. Calculating primary-code distinction involves subtracting the second highest RIASEC score from the highest RIASEC score. High levels of primary-code distinction suggest a meaningful difference exists between the top two types in a profile. Low levels of primary-code distinction suggest no meaningful difference exists between the top two types, and that the observed difference can be attributed to error in measurement.

*Consistency*

Consistency reflects the degree of relatedness between RIASEC types. The current study measures consistency by examining the degree of similarity between the first two codes of an individual’s three letter SDS summary code. Holland’s (1997) RIASEC hexagon provides a means by which to measure the degree of similarity. Letters adjacent to one another on the hexagon indicate the highest degree of consistency. Letters separated by one node on the hexagon indicate a moderate degree of consistency. Letters opposite one another on the hexagon indicate the lowest degree of consistency.

*Profile Elevation*

Profile elevation indicates the degree to which individuals have answered positively to items on the SDS. Low scores on profile elevation suggest individuals who
are not actively engaged in exploring work related interests. High scores on profile elevation suggest individuals who are actively engaged in exploring work related interests, and feel a sense of optimism with regard to work.

Data Collection Procedures

Orientation instructors from the College of Undergraduate Studies administered the SDS as a take home assignment to exploratory students during the fifth week of a 16 week semester. SDS booklets were then collected and reviewed during the next class. The SDS results were then entered into a database, which included individuals’ demographic details. A unique identifier allowed academic data, such as grade point average (GPA), and current major, to be related to individuals’ SDS results. The researcher exported the dataset into SPSS and Microsoft Excel to analyze the data.

Calculating Congruence

The researcher used the first part of the SDS to determine individuals’ expressed vocational interest. Individuals’ first occupational daydream was coded using the RIASEC typology. The primary RIASEC type determined an individual’s expressed vocational interest. The researcher used the second part of the SDS to determine individuals’ primary RIASEC type. This was determined by taking individuals’ highest RIASEC score. To calculate congruence, the researcher compared the primary RIASEC type associated with an individual’s first occupational daydream with his or her highest RIASEC score. A match between the two types indicated congruence, which the
researcher coded using the number one. A difference between the two types indicated incongruence, which the researcher coded using zero.

*Calculating Differentiation, Consistency and Profile Elevation*

The researcher calculated differentiation by subtracting individuals’ lowest RIASEC score from their highest RIASEC score. Consistency was determined by examining the proximity of an individual’s two highest RIASEC raw scores. Individuals with RIASEC types adjacent to one another on Holland’s hexagon reflected a high degree of consistency, and were coded in the dataset using the number three. Individuals with RIASEC types separated by one node on Holland’s hexagon reflected a moderate degree of consistency, and were coded in the dataset using the number two. Individuals with RIASEC types opposite one another on Holland’s hexagon reflected a low degree of consistency, and were coded in the dataset using the number one. The researcher calculated profile elevation by summing all six of the RIASEC scores in a profile.

*Data Analyses Procedures*

The SDS high-point code for an individual’s most recent occupational daydream represented the predictor variable. The SDS high-point code for an individual’s RIASEC profile represented the criterion variable. The researcher determined congruence by comparing the predictor and criterion variables for each participant. Participants were grouped based on their level of primary-code distinction. For example, participants who demonstrated a one point difference between their top two RIASEC types were grouped together, and participants with a two point difference between their top two types were
grouped together. This enabled the researcher to calculate the average percentage of congruence at each level of primary-code distinction. These numbers were plotted to determine if a relation existed between congruence and primary-code distinction. The researcher also analyzed certain two-letter pairs of SDS groups when sufficient data existed.

The researcher examined the “rule of eight” by using Chi-Square tests to determine how well primary-code distinction scores of eight points, or more, classified congruent and incongruent participants. Additional Chi-Square tests were used to determine how well primary-code distinction scores of 7 points, or more, and 9 points, or more, classified participants. A logistic regression was used to determine the significance of a relation between congruence and primary-code distinction. The logistic regression also allowed the researcher to analyze the relation between congruence and primary-code distinction while controlling for other variables, such as differentiation, consistency and profile elevation. Moderator variables were included in the analysis to test for interaction effects before considering main effects.
CHAPTER III

RESULTS

This chapter presents results of the descriptive and inferential analyses. The descriptive analysis describes all variables examined in the current study, including primary-code distinction, congruence, differentiation, consistency, profile elevation, and RIASEC Type. Descriptive measures include mean scores, standard deviations, ranges, and frequency distributions. This analysis also examined how variables such as primary-code distinction, differentiation, consistency, profile elevation, sex, and RIASEC type affect congruence. For example, charting rates of congruence by level of primary-code distinction, or consistency, provided a means by which to examine trends, and identify relations between the variables. Analyzing congruence by two-letter RIASEC type demonstrated the relative rates of congruence for each grouping. The inferential analyses test the hypotheses stated at the end of chapter two.

The researcher used logistic regression to determine the effects of the predictor variables, primary-code distinction, differentiation, consistency, profile elevation, and sex on the criterion variable, congruence. A post-hoc analyses added the variable RIASEC type to the original logistic regression model to test whether certain RIASEC types demonstrated greater congruence than others.
Descriptive Analyses

RIASEC Types

Table 1 displays mean scores and standard deviations for the six RIASEC scale scores for both the current study and Holland’s (1997) 1994 normative data. Interestingly, the descriptive statistics for these separate samples show remarkable similarities. For example, the mean score for the Realistic scale for males in the current study was 24.28, as compared to 24.31 for the Realistic scale for males in the 1994 normative sample. The mean scores for the other RIASEC types show similar consistencies. These similarities are listed as follows, where the first number indicates the mean for the current study, and the second number indicates the mean for the 1994 sample: Investigative (20.51, 22.56), Artistic (20.66, 19.21), Social (26.40, 27.43), Enterprising (26.42, 27.11), and Conventional (15.93, 18.22). The similarities between the two datasets provide evidence that RIASEC scale scores for participants in this study resemble those obtained for the normative reference sample.
Table 1

*Means and Standard Deviations for RIASEC Codes*

<table>
<thead>
<tr>
<th>RIASEC Mean Scores and Standard Deviations</th>
<th>Current Study</th>
<th>1994 Sample</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(N=2397)</td>
<td>(N=1114)</td>
</tr>
<tr>
<td>Type</td>
<td>M  SD</td>
<td>M  SD</td>
</tr>
<tr>
<td>R</td>
<td>18.12 8.42</td>
<td>19.2 9.5</td>
</tr>
<tr>
<td>I</td>
<td>18.41 9.21</td>
<td>21.2 10.3</td>
</tr>
<tr>
<td>A</td>
<td>21.03 11.29</td>
<td>20.6 10.8</td>
</tr>
<tr>
<td>S</td>
<td>29.57 9.37</td>
<td>30.5 9.9</td>
</tr>
<tr>
<td>E</td>
<td>25.24 10.29</td>
<td>26 10</td>
</tr>
<tr>
<td>C</td>
<td>17.04 9.09</td>
<td>20.4 10.2</td>
</tr>
</tbody>
</table>

Table 2

*Means and Standard Deviations for RIASEC Codes by Sex*

<table>
<thead>
<tr>
<th>Current Study</th>
<th>1994 Sample</th>
</tr>
</thead>
<tbody>
<tr>
<td>Females</td>
<td>Males</td>
</tr>
<tr>
<td></td>
<td>(N=1497)</td>
</tr>
<tr>
<td>Type</td>
<td>M  SD</td>
</tr>
<tr>
<td>R</td>
<td>11.95 6.6</td>
</tr>
<tr>
<td>I</td>
<td>16.3 8.82</td>
</tr>
<tr>
<td>A</td>
<td>21.4 10.93</td>
</tr>
<tr>
<td>S</td>
<td>32.73 9.14</td>
</tr>
<tr>
<td>E</td>
<td>24.06 10.18</td>
</tr>
<tr>
<td>C</td>
<td>18.14 9.28</td>
</tr>
</tbody>
</table>
Figure 7 displays the distribution of RIASEC high-point codes by sex. Female participants were most likely to resemble Social types (59%), and least likely to resemble Realistic types (1%). Males were likely to resemble either Social (24%), or Enterprising types (24%), followed closely by Realistic (22%), and Artistic (18%) types. Females demonstrated an uneven distribution of high-point codes when compared to the more even distribution of high-point codes for males. The distribution of high-point codes for females range from 1% to 59%, while the distribution of high-point codes for males range from 3% to 24%. The uneven distribution of female high-point codes suggests that female participants had a strong tendency to prefer Social interests and occupations. The more even distribution of male high-point codes suggests that they did not tend to prefer one specific type of interest or occupation over another. Given the differences in the distributions of high-point codes between males and females, one might therefore expect males to become employed in a wider variety of occupations than females.
Figure 7. Distribution of RIASEC High-Point Codes by Sex.
Figure 8 shows that the distribution of high-point codes for males in the current study resembles the pattern Holland (1997) reported for college males in the 1994 normative sample. The main differences occurred for Investigative and Artistic types. Holland found more male Investigative types in the 1994 sample than the researcher found in the current sample. Holland also found fewer Artistic types in the 1994 sample than the researcher found in the current sample. The similar patterns between the two samples provide evidence to support the reliability of the RIASEC scales for males.
Figure 8. Distribution of College Male RIASEC High-Point Codes for 1994 Normative Sample and the Current Sample.
Figure 9 shows that the distribution of high-point codes for females in the current study resembled the pattern Holland (1997) reported for college females in the 1994 normative sample. Similar to males, the frequency of female Investigative and Artistic high-point codes differ when compared to those from the 1994 sample. Holland found more female Investigative types than the researcher found in the current sample. Holland also found fewer Artistic types in the 1994 sample than the researcher found in the current sample. The greatest difference between the two samples occurred for female Conventional high-point codes, which show a 12% decrease. The similar patterns between the two samples provide evidence to support the reliability of the RIASEC scales for females.
Figure 9. Distribution of College Female RIASEC High-Point Codes for the 1994 Normative Sample and the Current Sample.
Primary-Code Distinction

Table 3 displays descriptive statistics for primary-code distinction, differentiation, consistency, and profile elevation for the entire sample. Table 4 displays the same information categorized by sex. Primary-code distinction measures the difference between a participant’s top two RIASEC scores. The researcher derived primary-code distinction by calculating the absolute difference between a participant’s highest two RIASEC scores. The overall mean score for primary-code distinction was 7.35, with a standard deviation of 6.23. Interestingly, this reveals that, on average, primary-code distinction scores fall below the benchmark of eight points suggested by Holland’s rule of eight. This lack of distinction suggests that, on average, one cannot determine an individual’s primary type when following Holland’s “rule of eight.” Furthermore, 1400 (58%) participants demonstrated primary-code distinction scores less than eight points, suggesting that the majority of the sample would not be able to determine their primary RIASEC type. Of the 1400 participants who demonstrated primary-code distinction scores less than eight points, 59% were women and 41% were men. Females ($M = 8.08, \sigma = 6.5$) demonstrated higher primary-code distinction scores than males ($M = 6.61, \sigma = 5.62$).
Table 3

Summary of Descriptive Statistics for all Participants (N=2397)

<table>
<thead>
<tr>
<th></th>
<th>M</th>
<th>SD</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Primary-code distinction</td>
<td>7.35</td>
<td>6.23</td>
<td>0</td>
<td>36</td>
</tr>
<tr>
<td>Differentiation</td>
<td>26.31</td>
<td>7.85</td>
<td>3</td>
<td>67</td>
</tr>
<tr>
<td>Consistency</td>
<td>2.57</td>
<td>.63</td>
<td>1</td>
<td>3</td>
</tr>
<tr>
<td>Profile Elevation</td>
<td>128.19</td>
<td>32.9</td>
<td>37</td>
<td>289</td>
</tr>
</tbody>
</table>

Table 4:

Summary of Descriptive Statistics by Sex

<table>
<thead>
<tr>
<th></th>
<th>Female (n=1497)</th>
<th>Male (n=900)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>M</td>
<td>SD</td>
</tr>
<tr>
<td>Primary-code distinction</td>
<td>8.08</td>
<td>6.5</td>
</tr>
<tr>
<td>Differentiation</td>
<td>26.28</td>
<td>7.85</td>
</tr>
<tr>
<td>Consistency</td>
<td>2.68</td>
<td>.55</td>
</tr>
<tr>
<td>Profile Elevation</td>
<td>124.58</td>
<td>31.25</td>
</tr>
</tbody>
</table>
Distinction Score Above and Below Eight Points

With more than half of the participants demonstrating primary-code distinction scores below eight points, further analyses examined congruence rates for primary-code distinction scores above and below the eight point threshold. The researcher categorized females into two groups, those with primary-code distinction scores less than eight points, and those with primary-code distinction scores greater than, or equal to, eight points. When primary-code distinction equals zero, one cannot determine congruence. Therefore, the researcher removed a total of 133 participants with primary-code distinction scores equal to zero from the analysis, leaving 1416 females, and 848 males. Results showed that there were slightly more females (741, 52%) with primary-code distinction scores less than eight points. More significantly, the average primary-code distinction score for this group was only 3.63. Therefore, on average, when female participants scored below the eight points suggested by Holland’s rule of eight, they scored well below that number. With such low average primary-code distinction scores, one might therefore expect this group to have few participants with congruent expressed interests. However, this was not the case. A total of 299 (40%) female participants with primary-code distinction scores below eight points demonstrated congruence. The average primary-code distinction score for female participants with primary-code distinction scores above eight points equaled 14. Therefore, on average, when female participants scored equal to, or above, the eight points suggested by Holland’s rule of eight, they scored well above that number. Of the 675 female participants with primary-
code distinction scores greater than, or equal to, eight points, 414 (61%) demonstrated congruence.

The researcher examined congruence for male participants in a similar manner, organizing males into two groups, those with primary-code distinction scores less than eight points and those with primary-code distinction scores greater than, or equal to, eight points. The majority of males (526, 62%) reported primary-code distinction scores less than eight points. The average primary-code distinction score for this group was only 3.5. Therefore, on average, when male participants scored below the eight points suggested by Holland’s rule of eight, they scored well below that number. With such low average primary-code distinction scores, one might therefore expect this group to have few participants with congruent expressed interests. However, this was not the case. A total of 197 (37.5%) male participants demonstrated congruence. The average primary-code distinction score for male participants with primary-code distinction scores equal to, or above, eight points, was 13. Therefore, on average, when male participants scored greater than, or equal to, the eight points suggested by Holland’s rule of eight, they scored well above that number. Of the 322 participants with primary-code distinction scores greater than, or equal to, eight points, 153 (47.5%) demonstrated congruence.

Analysis of Differentiation

Differentiation indicates the degree to which individuals resemble one RIASEC type over another. Measuring differentiation involved calculating the absolute difference between a participant’s highest and lowest RIASEC scores. The researcher recorded a
mean differentiation score of 26.31 for the entire sample, with a standard deviation of 7.85. Females \( M = 26.28, \sigma = 7.85 \) demonstrated higher mean scores on differentiation than males \( M = 24.85, \sigma = 7.64 \). These results resemble those reported by Holland (1997) for the 1994 normative sample, where females \( M = 27.72, \sigma = 7.48, n = 707 \) also demonstrated higher mean differentiation scores than males \( M = 25.59, \sigma = 7.96, n = 398 \).

The higher differentiation scores suggest that females possessed greater clarity about their vocational interests than males. With greater clarity, one might expect to see females make more congruent choices than males.

**Analysis of Consistency**

Consistency describes the similarity of an individual’s first two RIASEC types. Measuring consistency involved coding the variable as a discrete ordinal variable, where 1, 2, and 3 represented low, medium, and high, respectively. Individuals who demonstrate high consistency tend to have an easier time making choices because they do not have diverse conflicting vocational interests and goals. The researcher recorded an overall mean score for consistency of 2.57, with a standard deviation of .63. This indicates that participants, in general, demonstrated high consistency, and suggests that they experience less conflict when choosing interests and making vocational choices. On average, females \( M = 2.68, \sigma = .55 \) demonstrated higher consistency scores than males \( M = 2.38, \sigma = .71 \). Only 187 (8%) participants demonstrated low consistency. The majority, 1555 (65%), demonstrated high consistency, while 655 (27%)
demonstrated medium consistency. Given the large number of highly consistent participants, one would also expect to see a high number of participants with congruent expressed interests.

Figure 10 displays the distribution of consistency scores for males and females. A small percentage of females (4%) demonstrated low consistency, while the majority demonstrated high (72%) or medium (24%) consistency. Females (72%) demonstrated high consistency more often than males (53%). The results for females differ from the 1994 normative sample, where fewer females (59.1%) demonstrated high consistency, and more females (33.7%) demonstrated moderate consistency. The results for males were almost identical to the 1994 normative sample, where males demonstrated high (54.6%), moderate (32.1%), and low (13.3%) levels of consistency. The consistency results for the current sample suggest females experience less conflict regarding their vocational interests and goals. With more consistent interests, one might expect to see females make more congruent choices than males.
Figure 10. Consistency for Males and Females.
Analysis of Profile Elevation

Profile elevation measures the degree to which participants responded to the SDS with an optimistic response set of answers, i.e. yea-saying. Measuring profile elevation involved summing all six scores in an individual’s SDS results. Scores can range from a minimum of 14 to a maximum of 300, with high scores suggesting an optimistic and active individual, and low scores suggesting a possibly pessimistic, and inactive individual. The overall mean score for profile elevation was 128.19, with a standard deviation of 32.9. Males ($M = 134.2, \sigma = 34.51$) demonstrated higher profile elevation scores than females ($M = 124.58, \sigma = 31.25$). Males also demonstrated a far greater range of scores, scoring from 37 to 289, when compared to females, who scored from 41 to 231. The average profile elevation score for males in the current sample resembles the average profile elevation score for males from the 1994 normative sample, which reported an average score of 138.84. However, the average profile elevation score for females in the current sample is almost 10% lower than the average profile elevation score for females from the 1994 normative sample, which reported an average score of 137.14. Using the 1994 normative sample, Bullock and Reardon (2005) suggest average profile elevation scores for males range from 129 to 149, and average profile elevation scores for females range from 128 to 146. Few studies have examined profile elevation. Given the information available, the average profile elevation scores for males and females do not appear out of the ordinary. The higher scores for males suggests males possess a slightly more optimistic and active attitude toward their interests than females.
Analysis of Congruence

Congruence indicates whether or not a match exists between participants' inventoried type and their expressed vocational interest. Research suggests predictive validity increases when the two types match. The researcher measured congruence as a dichotomous variable, with “0” indicating incongruence, and “1” indicating congruence. Prior to examining congruence, the researcher removed all participants with a tie between their first and second RIASEC type from the analysis. This resulted in the removal of 133 cases, leaving 2264 participants in the analysis, 1416 females and 848 males. A total of 1063 (47%) participants demonstrated congruence, where their RIASEC type matched their expressed vocational interest. Of all females, 50% demonstrated congruence, while, 41% of all males demonstrated congruence.

Figure 11 shows the percent of congruence for each level of primary-code distinction. Congruence tends to increase as primary-code distinction scores increase. This trend appears linear between 0 and 24, after that score the trend appears to become non-linear. The non-linear trend occurs as a result of the small number of participants who demonstrate extremely high primary-code distinction scores, i.e. scores above 24. For example, if only two participants demonstrated a primary-code distinction score of 32, and neither individual is congruent, then the percentage of congruence for that level of primary-code distinction equals zero. Hence, extreme levels of primary-code distinction are less likely to demonstrate accurate ratios of congruence simply due to the small number of individuals at those levels. These results suggest a positive relation
exists between congruence and primary-code distinction. In addition, even at low levels of primary-code distinction, congruence appears to be relatively high. This suggests participants may achieve congruence even when their primary-code distinction scores fall below the threshold established by Holland’s “rule of eight.”
Figure 11. Percent of Congruence by Level of Primary-Code Distinction
With relatively few individuals demonstrating primary-code distinction scores above 25 points, a decision was made to examine congruence for participants with primary-code distinction scores below 26. The researcher chose this cut-off value because it includes all those individuals with primary-code distinction scores within three standard deviations of the mean. This resulted in the removal of 27 cases from the analysis. Figure 12 displays the resulting graph, and shows the percent of congruence by level of primary-code distinction. The graph suggests a positive relation exists between congruence and primary-code distinction, with congruence increasing as primary-code distinction increases. Interestingly, even at low levels of primary-code distinction, participants demonstrate relatively high rates of congruence. For example, when the primary-code distinction score equals four points congruence equals 45%. This ratio does not appear to change significantly at higher levels of primary-code distinction. For example, when the primary-code distinction score is twelve points congruence equals 48%. This represents a relatively small increase in congruence given the large increase in primary-code distinction.
Figure 12. Percent of Congruence by Level of Primary-Code Distinction for Primary-Code Distinction Scores Between 1 and 26 (n = 2237).
Figure 13 displays the percent of congruence by RIASEC type for the entire sample. Participants who resemble Investigative and Social types appear the most likely of all RIASEC types to demonstrate congruence, where the hit rate for both types equaled 56%. Participants who resemble Realistic and Conventional types appear the least likely of all RIASEC types to demonstrate congruence, where the hit rate for both types equaled 16%. Participants who resemble Artistic and Enterprising types demonstrated congruence rates of 48% and 42% respectively. The nature of the sample, i.e. college students from an institution that offers few Realistic or Conventional type majors, may help to explain these influenced these findings.
Figure 13. Percent of Congruence by RIASEC Type (n=2397).
Figure 14 displays the distribution of congruent types by gender. Females who most resembled the Social type (57%) tended to demonstrate congruence more often than males who most resembled the Social type (51%). In addition, females who most resembled the Investigative type (61%) tended to demonstrate congruence more often than males who most resembled the Investigative type (52%). Males who most resembled the Conventional type (23%) tended to demonstrate congruence more often than females who most resembled the Conventional type (13%). In addition, males who most resembled the Artistic type (55%) tended to demonstrate congruence more often than females who most resembled the Artistic type (43%). Males and females who most resembled Realistic or Enterprising types demonstrated similar rates of congruence. Participants who demonstrated the greatest rates of congruence tended to be female and resembled either the Investigative, or Social types.
Figure 14. Congruent Types by Gender.
Table 5 displays descriptive statistics for congruence by two-letter RIASEC types. The researcher calculated congruence by comparing a participant’s inventoried type to his or her expressed vocational interest. The first letter of a participant’s SDS profile provided the data for the inventoried type. The first letter of a participant’s most recent occupational daydream provided the data for the expressed vocational interest. A hit was recorded, and coded with a “1”, if the participant’s inventoried type matched his or her expressed vocational interest. A miss was recorded, and coded with a “0”, if the participant’s inventoried type did not match his or her expressed vocational interest. Table 5 displays the data sorted in descending order by the total count for each two-letter type. The most common two-letter types were SE, SA, ES and SA, which accounted for 52% of all participants. IC types demonstrated the highest percentage of congruence, 88%. However, only eight participants have an IC two-letter type, making this statistic unreliable. SC types, which were far more common (n=111), demonstrated the next highest percentage of congruent matches with 67%. IS and AR types also show high levels of congruence, both demonstrating 61% congruence. A more detailed analysis examined several common two-letter types. The researcher created graphs to examine the percent of matches at different levels of primary-code distinction for SE, ES, SA, AS, SC, IS, and AR.
### Table 5

*Descriptive Data for Two-Letter RIASEC Types (n=2264)*

<table>
<thead>
<tr>
<th>Two Letter RIASEC Types</th>
<th>Average Primary-code Distinction</th>
<th># of Matches</th>
<th>Total Count</th>
<th>% of Matches</th>
</tr>
</thead>
<tbody>
<tr>
<td>SE</td>
<td>9.35</td>
<td>283</td>
<td>485</td>
<td>58%</td>
</tr>
<tr>
<td>SA</td>
<td>9.25</td>
<td>152</td>
<td>289</td>
<td>53%</td>
</tr>
<tr>
<td>ES</td>
<td>6.45</td>
<td>100</td>
<td>217</td>
<td>46%</td>
</tr>
<tr>
<td>AS</td>
<td>6.78</td>
<td>90</td>
<td>197</td>
<td>46%</td>
</tr>
<tr>
<td>SI</td>
<td>9.8</td>
<td>58</td>
<td>122</td>
<td>48%</td>
</tr>
<tr>
<td>SC</td>
<td>9.52</td>
<td>74</td>
<td>111</td>
<td>67%</td>
</tr>
<tr>
<td>AE</td>
<td>7.43</td>
<td>31</td>
<td>69</td>
<td>45%</td>
</tr>
<tr>
<td>RE</td>
<td>8.03</td>
<td>11</td>
<td>65</td>
<td>17%</td>
</tr>
<tr>
<td>IS</td>
<td>7.14</td>
<td>36</td>
<td>59</td>
<td>61%</td>
</tr>
<tr>
<td>SR</td>
<td>6.22</td>
<td>27</td>
<td>54</td>
<td>50%</td>
</tr>
<tr>
<td>CE</td>
<td>6.66</td>
<td>10</td>
<td>53</td>
<td>19%</td>
</tr>
<tr>
<td>AI</td>
<td>7.22</td>
<td>26</td>
<td>51</td>
<td>51%</td>
</tr>
<tr>
<td>RS</td>
<td>9.54</td>
<td>7</td>
<td>50</td>
<td>14%</td>
</tr>
<tr>
<td>EC</td>
<td>6.19</td>
<td>18</td>
<td>48</td>
<td>38%</td>
</tr>
<tr>
<td>RI</td>
<td>8.52</td>
<td>10</td>
<td>48</td>
<td>21%</td>
</tr>
<tr>
<td>ER</td>
<td>5.58</td>
<td>21</td>
<td>43</td>
<td>49%</td>
</tr>
<tr>
<td>EI</td>
<td>5.41</td>
<td>8</td>
<td>37</td>
<td>22%</td>
</tr>
<tr>
<td>AR</td>
<td>8.22</td>
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<td>IA</td>
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</tr>
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<td>EA</td>
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<td>31%</td>
</tr>
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<td>IR</td>
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<td>CS</td>
<td>4.42</td>
<td>5</td>
<td>33</td>
<td>15%</td>
</tr>
<tr>
<td>RA</td>
<td>6.94</td>
<td>4</td>
<td>33</td>
<td>12%</td>
</tr>
<tr>
<td>IE</td>
<td>7.95</td>
<td>13</td>
<td>22</td>
<td>59%</td>
</tr>
<tr>
<td>CI</td>
<td>6.18</td>
<td>1</td>
<td>11</td>
<td>9%</td>
</tr>
<tr>
<td>IC</td>
<td>7.63</td>
<td>7</td>
<td>8</td>
<td>88%</td>
</tr>
<tr>
<td>RC</td>
<td>5.5</td>
<td>1</td>
<td>6</td>
<td>17%</td>
</tr>
<tr>
<td>AC</td>
<td>9.17</td>
<td>3</td>
<td>6</td>
<td>50%</td>
</tr>
<tr>
<td>CA</td>
<td>3.75</td>
<td>0</td>
<td>4</td>
<td>0%</td>
</tr>
<tr>
<td>CR</td>
<td>10.33</td>
<td>1</td>
<td>3</td>
<td>33%</td>
</tr>
</tbody>
</table>
Figure 15 displays the distribution of congruence at different levels of primary-code distinction for all SE types. The average percentage of congruence equals 61%. The trend appears linear, where the chance of congruence increases as primary-code distinction increases. The graph of SE types also demonstrates that high levels of congruence can be achieved even at low levels of primary-code distinction. For example, when primary-code distinction equals just two points, congruence for SE types equals 41%. One might well consider this to be a high rate of congruence given the relatively small difference in scores between Social and Enterprising types.
Figure 15. Percent of Matches by Level of Primary-Code Distinction for SE Types (n=485).
Figure 16 displays the distribution of congruence at different levels of primary-code distinction for all ES types. The average percentage of congruence equals 46%. The trend appears linear, where the chance of congruence increases as primary-code distinction increases. As observed with SE types, ES types demonstrated relatively high levels of congruence at low levels of primary-code distinction. For example, when primary-code distinction equals four points, congruence for ES types equals 42%. One might well consider this to be a high rate of congruence given the relatively small difference in scores between Enterprising and Social types.
Figure 16. Percent of Matches by Level of Primary-Code Distinction for ES Types.
Figure 17 displays the distribution of congruence at different levels of primary-code distinction for all SA types. The average percentage of congruence equals 53%. The trend appears linear, where the chance of congruence increases as primary-code distinction increases. As observed with ES and SE types, SA types demonstrate relatively high levels of congruence at low levels of primary-code distinction. For example, when primary-code distinction equals 4 points, the percent of congruent participants equals 53%. This suggests once more that congruence can be achieved before primary-code distinction equals eight points, the amount suggested by Holland’s “rule of eight”.
Figure 17. Percent of Matches by Level of Score Distinction for SA Types (n=289).
Figure 18 displays the distribution of congruence at different levels of primary-code distinction for all AS types. The average percentage of congruence equals 46%, reflecting a moderate degree of congruence. The trend appears linear, where the chance of congruence increases as primary-code distinction increases. Similar to SE, ES and SA types, AS types demonstrated a relatively high level of congruence at low levels of primary-code distinction. For example, when primary-code distinction equals 4 points, the percent of congruent participants equals 45%. This suggest once more that congruence can be achieved before primary-code distinction equals eight points, as suggested by Holland’s rule of eight. The researcher found similar results for SC, IS, and AR two-letter types.
Figure 18. Percent of Matches by Level of Score Distinction for AS Types (n=197).
Inferential Analysis

The researcher studied the “rule of eight” by using Chi-Square analyses to determine how well primary-code distinction scores classified congruent and incongruent participants. The first Chi-Square test examined how well primary-code distinction scores of seven points, or more, classified congruent and incongruent participants. The researcher created a dichotomous variable, GTE7, where zero equals participants with primary-code distinction scores less than seven points, and one equals participants with primary-code distinction scores greater than, or equal to, seven points. The variable, GTE7, represented the independent variable, while congruence represented the dependent variable. The Chi-Square test returned a significant result, $\chi^2(1, N = 2237) = 74.3, p < .001$, which suggests that the dependent variable, congruence, is not independent of the predictor variable, i.e. participants with primary-code distinction scores of seven points or more.

The second Chi-Square test examined how well primary-code distinction scores of eight points, or more, classified congruent and incongruent participants. The researcher created a dichotomous variable, GTE8, where zero equals participants with primary-code distinction scores less than eight points, and one equals participants with primary-code distinction scores greater than, or equal to, eight points. The variable, GTE8, represented the independent variable, while congruence represented the dependent variable. The Chi-Square test returned a significant result, $\chi^2(1, N = 2237) = 68.8, p < .001$, which suggests
that the dependent variable, congruence, is not independent of the predictor variable, i.e. participants with primary-code distinction scores of eight points or more.

The third Chi-Square test examined how well primary-code distinction scores of nine points, or more, classified congruent and incongruent participants. The researcher created a dichotomous variable, GTE9, where zero equals participants with primary-code distinction scores less than nine points, and one equals participants with primary-code distinction scores greater than, or equal to, nine points. The variable, GTE9, represented the independent variable, while congruence represented the dependent variable. The third Chi-Square test also returned a significant result, $\chi^2(1, N = 2237) = 76.5, p < .001$, which suggests that the dependent variable, congruence, is not independent of the predictor variable, i.e. participants with primary-code distinction scores of nine points or more.

Table 6 displays a classification table of predicted and observed results on the dependent variable, congruence. These results help to determine sensitivity and specificity. Sensitivity and specificity refer to statistical measures that examine how well a dichotomous classification test, in this case, Chi-Square, correctly identifies an outcome. The sensitivity statistic calculates the probability that the test will return a positive result among participants who have the condition, i.e. participants who demonstrate primary-code distinction scores greater than, or equal to, seven, eight, or nine points, respectively. Sensitivity in the current study refers to the probability that participant, who are in fact congruent, will be classified as congruent. The specificity statistic calculates the probability that the test will return a negative result for participants
who do not have the condition, i.e. participants who demonstrate primary-code distinction scores less than seven, eight, or nine points, respectively. Specificity in the current study refers to the probability that participants, who are in fact incongruent, will be classified as incongruent.

These statistics provide a measure of power, which helps to determine the practical significance of the independent variable. The variable GTE7 correctly predicts congruence 56% of the time, while the variable GTE8, correctly predicts congruence 53% of the time, and the variable GTE9 correctly predicts congruence 59% of the time. The variable GTE7 correctly predicts incongruence 59% of the time, while the variable GTE8, correctly predicts congruence 65% of the time, and the variable GTE9 70% of the time. These results suggest the independent variables predict incongruence better than they predict congruence. More importantly, the variables GTE7, and GTE9 predict congruence better than GTE8, which suggests the “rule of seven”, or the “rule of nine”, may be more accurate than the “rule of eight.” These statistics, while useful, do not provide detailed information regarding how congruence changes at different levels of primary-code distinction. The researcher used logistic regression to examine how a one point increase in primary-code distinction affected congruence.
Table 6

*Classification of Observed and Predicted Values on Congruence for Primary-Code*

*Distinction Scores Greater Than, or Equal to 7, 8, and 9 Points*

<table>
<thead>
<tr>
<th></th>
<th>Observed</th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>GTE7</td>
<td>GTE8</td>
<td>GTE9</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Predicted Congruent Incongruent</td>
<td>Congruent Incongruent</td>
<td>Congruent Incongruent</td>
<td>Congruent Incongruent</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Congruent</td>
<td>617</td>
<td>484</td>
<td>551</td>
<td>419</td>
<td>500</td>
<td>354</td>
</tr>
<tr>
<td>Incongruent</td>
<td>430</td>
<td>706</td>
<td>496</td>
<td>771</td>
<td>547</td>
<td>836</td>
</tr>
<tr>
<td>Sensitivity</td>
<td>56%</td>
<td></td>
<td>53%</td>
<td></td>
<td>59%</td>
<td></td>
</tr>
<tr>
<td>Specificity</td>
<td>59%</td>
<td></td>
<td>65%</td>
<td></td>
<td>70%</td>
<td></td>
</tr>
</tbody>
</table>
The researcher used direct logistic regression analysis to regress congruence, the outcome variable, against the predictor variables: primary-code distinction, consistency, profile elevation, and sex. As will be discussed later, the researcher removed the variable differentiation from the analysis because of problems with collinearity. The analysis also included the moderators: primary-code distinction by consistency, and primary-code distinction by profile elevation. Variables were centered, where appropriate, to reduce problems associated with multicollinearity. Centering variables involves calculating the mean for a variable, and then subtracting that amount from each data value in the dataset for that particular variable. The researcher centered the variables, primary-code distinction, consistency, and profile elevation before running the model using SPSS. One hundred and thirty three cases were found to have a value of zero for primary-code distinction, indicating a tie between the top two-letters in the RIASEC profile. These cases were removed from subsequent analysis because it was not possible to determine congruence or incongruence for the participants. The researcher did not find any cases with missing values. Analysis of primary-code distinction boxplots suggested the existence of outliers. A decision was made to remove primary-code distinction values greater than three standard deviations above the mean. This resulted in twenty seven cases being removed from subsequent analysis, leaving a total of 2237 cases in the dataset, with 1396 females and 841 males.

Table 7 displays collinearity statistics for all predictor variables tested. Results suggest no evidence of multicollinearity. Table 8 displays correlations between all
predictor variables. A significant moderate linear relation exists between primary-code
distinction and differentiation, where $r = .47$. This statistic suggests that the two variables
are not independent of one another. This is not surprising given that primary-code
distinction measures the absolute difference between the top two scores in the RIASEC
profile, while differentiation measures the absolute difference between the highest and
lowest scores in the RIASEC profile. The researcher made the decision to remove the
differentiation variable from the analysis because including this variable might lead to
redundancy. The primary-code distinction variable remained in the model because it was
the variable of primary interest for the current study. The researcher removed all
interaction terms from the model after running the analysis, because results suggested
they had no significant effect on the outcome variable.
Table 7

**Collinearity Statistics**

<table>
<thead>
<tr>
<th>Predictor Variable</th>
<th>Tolerance</th>
<th>VIF</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sex</td>
<td>0.91</td>
<td>1.1</td>
</tr>
<tr>
<td>Consistency</td>
<td>0.931</td>
<td>1.074</td>
</tr>
<tr>
<td>Profile Elevation</td>
<td>0.792</td>
<td>1.263</td>
</tr>
<tr>
<td>Differentiation</td>
<td>0.641</td>
<td>1.56</td>
</tr>
<tr>
<td>PCD*</td>
<td>0.667</td>
<td>1.5</td>
</tr>
</tbody>
</table>

* PCD = primary-code distinction

Table 8

**Correlations Between Predictor Variables (n = 2239)**

<table>
<thead>
<tr>
<th></th>
<th>Sex</th>
<th>PCD</th>
<th>Consistency</th>
<th>Profile Elevation</th>
<th>Differentiation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sex</td>
<td>1</td>
<td>-.12**</td>
<td>-.22**</td>
<td>.14**</td>
<td>-.15**</td>
</tr>
<tr>
<td>PCD</td>
<td>1</td>
<td>0.04</td>
<td>-.22**</td>
<td>.47**</td>
<td></td>
</tr>
<tr>
<td>Consistency</td>
<td>1</td>
<td>-.04*</td>
<td>.15**</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Profile</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Elevation</td>
<td></td>
<td></td>
<td>.2**</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Differentiation</td>
<td></td>
<td></td>
<td></td>
<td>1</td>
<td></td>
</tr>
</tbody>
</table>

*. Correlation is significant at the 0.05 level (2-tailed).

**. Correlation is significant at the 0.01 level (2-tailed).

PCD = primary-code distinction
The researcher ran a test of the full model, which included the predictors: primary-code distinction, profile elevation, consistency and sex, against a constant-only model. Results showed the model to be statistically reliable

\[ \chi^2(6, N = 2237) = 134.69, p < .001 \]

indicating that the predictors, as a set, adequately fit the data. This suggests that the set of predictors reliably distinguished between congruent and incongruent participants. The Cox and Snell R-Square, an approximation of ordinary least squares R-squared, equaled .058, which suggests that the full model only accounts for a small amount of the variance in congruence, i.e. 5.8%.

Table 9 displays a classification table of predicted and observed results on the dependent variable, congruence. These results help to determine the sensitivity and specificity of the model. Sensitivity and specificity refer to statistical measures that examine how well a dichotomous classification test, in this case, the logistic regression model, correctly identifies an outcome. The sensitivity statistic calculates the probability that the test will return a positive result among participants who have the condition. Sensitivity in the current study refers to the probability that a participant, who is in fact congruent, will be classified as congruent by the model. The specificity statistic calculates the probability that the test will return a negative result for participants who do not have the condition. Specificity in the current study refers to the probability that a participant, who is in fact incongruent, will be classified as incongruent by the model. These statistics provide a measure of power, which helps to determine the practical significance of the model. The sensitivity statistic for the model equals 43.5%, while
specificity equals 75.8%. These results suggest that the model does a better job at predicting incongruent participants than congruent participants.
Table 9

Classification of Observed and Predicted Values on Congruence Between Expressed Vocational Interest and SDS High-Point Code

<table>
<thead>
<tr>
<th>Predicted</th>
<th>Congruent</th>
<th>Incongruent</th>
</tr>
</thead>
<tbody>
<tr>
<td>Congruent</td>
<td>455</td>
<td>288</td>
</tr>
<tr>
<td>Incongruent</td>
<td>592</td>
<td>902</td>
</tr>
</tbody>
</table>

Sensitivity 43.50%

Specificity 75.80%
Table 10 displays the results of the logistic regression analysis. The results list only those variables that had significant effects. Significant main effects were found for primary-code distinction \((p < .001)\), consistency \((p < .01)\), and sex \((p < .05)\). Table 10 also reports the results for the logistic regression as exponentiated coefficients, \(\text{Exp}(B)\), also commonly referred to as odds ratios. An \(\text{Exp}(B)\) value greater than 1 indicates an increase in the odds of finding congruence between expressed vocational interest and SDS high-point code. An \(\text{Exp}(B)\) value less than 1 indicates a decrease in the odds of finding congruence between expressed vocational interest and SDS high-point code. An \(\text{Exp}(B)\) value equal to 1 indicates no change in the odds of finding congruence between expressed vocational interest and SDS high-point code. Examining the exponentiated coefficients, the researcher found that an increase of one point in primary-code distinction would result in an increase of 8\% in the likelihood of congruence. An increase of one point in consistency would result in an increase of 22\% in the likelihood of congruence. Finally, male participants decrease their likelihood of being congruent by 17\% when compared to female participants.
Table 10

*Logistic Regression Results (n = 2237)*

<table>
<thead>
<tr>
<th></th>
<th>B</th>
<th>Exp (B)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Primary-code distinction</td>
<td>0.07</td>
<td>1.08***</td>
</tr>
<tr>
<td>Consistency</td>
<td>0.2</td>
<td>1.22**</td>
</tr>
<tr>
<td>Sex a</td>
<td>-0.19</td>
<td>0.83*</td>
</tr>
<tr>
<td>Constant</td>
<td>-0.25</td>
<td>0.78***</td>
</tr>
<tr>
<td>R-Squared</td>
<td></td>
<td>0.58</td>
</tr>
</tbody>
</table>

* p < .05; ** p < .01; *** p < .001 (two-tailed test)

a Compared to Females
Post-Hoc Analysis

Results from the descriptive analysis suggested that the variable RIASEC type affects the likelihood of participants demonstrating congruence. The researcher decided to test the effect of RIASEC type by including the variable in the logistic regression model. Direct logistic regression analysis was used to regress congruence, the outcome variable, against the predictor variables: primary-code distinction, consistency, profile elevation, sex, and RIASEC type. Table 11 displays collinearity statistics for all predictor variables tested. Results suggest no evidence of multicollinearity. Table 12 displays correlations between all predictor variables tested. Results suggest the variables are independent of one another.
Table 11

**Collinearity Statistics**

<table>
<thead>
<tr>
<th>Predictor Variable</th>
<th>Tolerance</th>
<th>VIF</th>
</tr>
</thead>
<tbody>
<tr>
<td>RIASEC Type</td>
<td>0.925</td>
<td>1.081</td>
</tr>
<tr>
<td>Sex</td>
<td>0.884</td>
<td>1.132</td>
</tr>
<tr>
<td>Consistency</td>
<td>0.947</td>
<td>1.056</td>
</tr>
<tr>
<td>Profile Elevation</td>
<td>0.936</td>
<td>1.069</td>
</tr>
<tr>
<td>PCD</td>
<td>0.936</td>
<td>1.069</td>
</tr>
</tbody>
</table>

*PCD = primary-code distinction

Table 12

**Correlations Between Predictor Variables (n = 2239)**

<table>
<thead>
<tr>
<th></th>
<th>Sex</th>
<th>PCD</th>
<th>Consistency</th>
<th>Profile Elevation</th>
<th>RIASEC Type</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sex</td>
<td>1</td>
<td>-0.12**</td>
<td>-0.22**</td>
<td>0.14**</td>
<td>0.25**</td>
</tr>
<tr>
<td>PCD</td>
<td>1</td>
<td>0.04</td>
<td>-0.22**</td>
<td>-0.12**</td>
<td></td>
</tr>
<tr>
<td>Consistency</td>
<td>1</td>
<td>0.04</td>
<td>-0.12**</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Profile Elevation</td>
<td>1</td>
<td></td>
<td></td>
<td>0.08**</td>
<td></td>
</tr>
<tr>
<td>RIASEC Type</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

*. Correlation is significant at the 0.05 level (2-tailed).
**. Correlation is significant at the 0.01 level (2-tailed).

PCD = primary-code distinction
A test of the full model against a constant-only model was found to be statistically reliable $\chi^2(11, N = 2237) = 272.85, p < .001$, indicating that the predictors, as a set, adequately fit the data. This suggests that the set of predictors reliably distinguished between congruent and incongruent participants. The Cox and Snell R-Square, an approximation of ordinary least squares R-squared, was .115, which suggests that the full model still only accounts for a small amount of the variance in congruence, 11.5%. However, adding the variable RIASEC type doubled the amount of explained variance. Table 13 displays a classification table of predicted and observed results on the dependent variable, congruence. These results can be used to determine the sensitivity and specificity of the model. The sensitivity statistic for the model is 54%, while specificity is 70%. These results suggest that the model is more effective at predicting participants who are incongruent than participants who are congruent.
Table 13

*Classification of Observed and Predicted Values on Congruence Between Expressed Vocational Interest and SDS High-Point Code*

<table>
<thead>
<tr>
<th>Predicted</th>
<th>Congruent</th>
<th>Incongruent</th>
</tr>
</thead>
<tbody>
<tr>
<td>Congruent</td>
<td>566</td>
<td>358</td>
</tr>
<tr>
<td>Incongruent</td>
<td>481</td>
<td>832</td>
</tr>
<tr>
<td>Sensitivity</td>
<td>54%</td>
<td></td>
</tr>
<tr>
<td>Specificity</td>
<td>70%</td>
<td></td>
</tr>
</tbody>
</table>
Table 14 shows the results of the logistic regression analysis. The model includes only significant effects. A significant main effect was found for primary-code distinction, \((p < .001)\). A significant main effect was found for RIASEC type, where Social types were found to be significantly different from Realistic and Conventional types \((p < 0.001)\), and also significantly different from Enterprising types \((p < 0.01)\). Table 14 also reports the results for logistic regression as exponentiated coefficients \((\text{Exp} (B))\). Results suggest that an increase of one point in primary-code distinction would result in an increase of 8% in the likelihood of a participant demonstrating congruence.

Analysis of the variable RIASEC type used Social type as the base comparison. The researcher chose Social as the comparison type because the vast majority of participants had Social as one of their top two RIASEC letters. Furthermore, Social types were seen to be among the most congruent of all types. Results suggest that Realistic, Conventional, and Enterprising types significantly predict the odds of being congruent, when compared to Social types. Realistic types were 85% less likely to demonstrate congruence than Social types. Conventional types were 82% less likely to demonstrate congruence than Social types. Enterprising types were 32% less likely to demonstrate congruence than Social types. These results suggest that participants with SDS high-point codes of Realistic or Conventional are much less likely to demonstrate congruent expressed interests than participants with a SDS high-point code that is Social. Enterprising types were also less likely to be congruent when compared to Social types. However, the odds did not decrease as much as they did for Realistic and Conventional
types. Therefore, primary-code distinction and RIASEC type both influenced the likelihood of a participant being congruent.
Table 14

*Logistic Regression Results (n = 2237)*

<table>
<thead>
<tr>
<th></th>
<th>B</th>
<th>Exp (B)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Primary-code distinction</td>
<td>0.07</td>
<td>1.08***</td>
</tr>
<tr>
<td>RIASEC Type (R)\textsuperscript{a}</td>
<td>-1.91</td>
<td>.15***</td>
</tr>
<tr>
<td>RIASEC Type (E)\textsuperscript{a}</td>
<td>-0.38</td>
<td>.68**</td>
</tr>
<tr>
<td>RIASEC Type (C)\textsuperscript{a}</td>
<td>-1.75</td>
<td>.18***</td>
</tr>
<tr>
<td>Constant</td>
<td>-0.59</td>
<td>.55***</td>
</tr>
<tr>
<td>R-Squared</td>
<td></td>
<td>0.115</td>
</tr>
</tbody>
</table>

\textsuperscript{a} Compared to Social types

\*p < .05; **p < .01; ***p < .001 (two-tailed test)
Summary

This chapter presented the results of the descriptive statistics and inferential analyses conducted for the current study. The researcher found similarities between the descriptive statistics derived from the current dataset, and the 1994 normative dataset, published by Holland (1997). These similarities provide evidence of the reliability of the SDS over time. The descriptive statistics suggest females tend to demonstrate more Social interests than males, while males tend to demonstrate more Realistic interests than females. Participants who resembled Investigative or Social types were the most likely to demonstrate congruence, while participants who resembled Realistic or Conventional were the least likely to demonstrate congruence. Analysis of primary-code distinction suggests participants, on average, score below the eight point threshold identified by the “rule of eight.” When participants reported primary-code distinction scores less than eight points, they reported scores well below this threshold. Despite such low primary-code distinction scores, almost half of these participants demonstrated congruence.

The inferential analysis, which used logistic regression, found the variables primary-code distinction, consistency, and sex to be significant predictors of congruence. A post-hoc analysis added the variable RIASEC type to the model. Results of the post-hoc analysis suggest that RIASEC type was a significant predictor of congruence. However, in adding RIASEC type to the model, the variables consistency, and sex became non-significant. Subsequently, primary-code distinction and RIASEC became the only variables left in the model that explained a significant amount of the variance in
congruence. This model accounted for twice as much of the variance in congruence as the original model. Overall, the predictors tended to predict incongruence better than congruence. Chapter four provides conclusion and attempts to interpret the results found in this chapter.
CHAPTER IV
DISCUSSION

This chapter provides a review of the current study, and begins by explaining the purpose of this research. The researcher presents conclusions using the results reported in chapter three, and interprets these results accordingly. Implications for research and practice are presented. The researcher identifies limitations to the study, and discusses the boundaries within which interpretations and implications should be considered. The chapter concludes by suggesting ideas for future research.

In an effort to test and improve interpretative guidelines for the SDS, this study examined the “rule of eight.” The “rule of eight”, which is based on the standard error of measurement for the SDS, suggests that two RIASEC types within individuals’ profiles cannot be considered distinct unless at least eight points separate the two. Examining the distinctiveness between SDS scores helps to order an individual’s resemblance to each of the RIASEC types. The ordering of types assists in identifying which occupations individuals appears most suited for. Despite a large body of literature examining the SDS, and the constructs upon which it relies, no studies have examined the “rule of eight.” The current study addressed this gap in the literature, and in doing so, sought to improve interpretative guidelines for the SDS.

The researcher examined the “rule of eight” as it applied to the first two letters of participants’ SDS summary codes, which contain the three highest letters in their SDS profile. Although all three letters in the summary code should be considered, career
practitioners attend particularly to the first two types because these determine the
dominant RIASEC type. Studying the “rule of eight” involved examining congruence
between participants’ expressed and inventoried vocational interests at different levels of
primary-code distinction. The primary type associated with participants’ first
occupational daydream represented their expressed vocational interest. The highest score
in the SDS profile represented participants’ inventoried interest. Primary-code distinction
represented the numerical difference between participants’ top two RIASEC scores.
Participants demonstrated congruence when the RIASEC type associated with their
expressed vocational interest matched the RIASEC type associated with their inventoried
interest.

The researcher hypothesized that primary-code distinction could be used to
predict congruence, and also test the “rule of eight.” Both descriptive statistics and
inferential analyses were used to examine the relation between primary-code distinction
and congruence. The researcher included additional predictor variables in the inferential
analyses in an attempt to isolate the relative impact of primary-code distinction on
congruence. These variables included differentiation, consistency, profile elevation, and
sex. The analysis also tested for interaction effects that might moderate the relation
between primary-code distinction and congruence. These moderators included primary-
code distinction by consistency, and primary-code distinction by profile elevation. The
researcher ran descriptive statistics for all variables in the study, and used logistic
regression to model both predictors and moderators against the criterion variable,
congruence. This type of analysis allowed the researcher to examine how primary-code distinction affected congruence, while controlling for other variables such as differentiation, consistency, profile elevation, and sex.

Conclusions

The first hypothesis stated that congruence between RIASEC type and expressed vocational interest is greater for individuals whose degree of primary-code distinction equals or exceeds eight points. This means that when participants’ top two SDS scores differ by less than eight points, a primary SDS type cannot be determined. Scores that differ by eight points, or more, reflect meaningful differences because they cannot be attributed to error in measurement. The SEM shows degree of statistical certainty, but this does not necessarily translate into validity for the use of a “rule of eight”. When scores differ by eight points, or more, we would expect participants’ expressed vocational interest to be congruent with their primary SDS type. With a difference of less than eight points, we expect the expressed interest to be equally congruent with the either their first or second SDS letter.

For the SDS, the SEM helps to determine when a difference in scores between RIASEC types reflects a reliable and meaningful difference. For example, consider the profile for a participant with the following SDS summary code, Enterprising = 46, Social = 42, and Conventional = 31. The difference between the top two scores equals 4 points, and because this falls within the SEM, we cannot say with confidence which type the participant most resembles. This means that this participant’s profile may be either ESC,
or SEC. Given this uncertainty, we would expect participants with scores below the SEM to be less likely to demonstrate a congruent match between their primary inventoried type and the primary type associated with their first vocational aspiration.

Results from the descriptive analysis showed that, on average, participants with primary-code distinction scores greater than, or equal to, eight points, demonstrated congruence more often than those with primary-code distinction scores less than eight points. This suggests that the ‘rule of 8’ does help to determine when a difference between participants’ top two RIASEC types reflects a meaningful difference. However, the descriptive statistics show that a large number of participants with primary-code distinction scores less than eight points also demonstrated congruence. The researcher decided to use Chi-square tests to examine the predictive ability of the “rule of eight”, while also examining other potential primary-code distinction threshold scores.

Three Ch-Square tests examined whether three different primary-code distinction threshold scores could correctly classify participants as congruent or incongruent. The primary-code distinction scores used included seven, eight, and nine, points which one could interpret as the “rule of seven”, the “rule of eight”, and the “rule of nine”, respectively. Results showed that the all tests were significant, which means that each of the “rules” could be used to correctly classify congruent and incongruent participants. However, while the “rule of nine” demonstrated the best classification rate, the “rule of seven” proved to classify participants better than the “rule of eight.” Trying to determine exactly how many primary-code distinction points represent a meaningful difference
between types may not be the best way to identify when a difference represents a significant difference. The Chi-Square tests, although revealing, require that the primary variable of interest, primary-code distinction, be coded as a categorical variable. It is better to code primary-code distinction as a continuous variable because it allows for greater variability in scores. Furthermore, it allows one to examine the relative impact of a single point increase in primary-code distinction. Therefore, the researcher ran descriptive and inferential analyses of congruence, with primary-code distinction coded as a continuous type variable.

The descriptive statistics show that a linear positive relation exists between primary-code distinction and congruence. This means that, as primary-code distinction increases, participants show a tendency to demonstrate a match between their primary inventoried type and the primary type associated with their expressed vocational interest. Furthermore, the statistics show that participants demonstrate congruence before primary-code distinction scores reach eight points. The average primary-code distinction score for all participants in the sample equaled 7.35, a value that falls below the eight points suggested by the “rule of eight.” If we used the “rule of eight” in the strictest sense, we would not be able to determine the dominant RIASEC type for any of the participants in the current sample. Subsequently, we would expect to see a low rate of congruence. However, almost half of all participants (47%) demonstrated congruence. More importantly, 40% of those participants who demonstrated primary-code distinction scores below eight points demonstrated congruence. If the rule of eight were in fact true, we
would not expect to see such a high percentage of congruent individuals with primary-code distinction scores less than eight points.

The average primary-code distinction score for participants who scored below eight points equaled 3.93. Therefore, when participants scored below eight points, on average, they scored well below this margin. Given such low primary-code distinction scores, one might expect to see these participants also demonstrate a low level of congruence. However, the descriptive statistics show that 45% of participants with primary-code distinction scores equal to four points demonstrated congruence. Although congruence increased as primary-code distinction increased, the increase in congruence appears relatively small when compared to the increase in primary-code distinction. For example, when the primary-code distinction score increased to twelve points, congruence only increased to 48%. These results show that small differences in primary-code distinction can still reflect meaningful differences between participants’ top two RIASEC types.

The researcher also analyzed congruence and primary-code distinction scores for a number of two-letter types, including, SE, ES, SA, AS, SC, IS, and AR types. Each of the two-letter types displayed high rates of congruence at low levels of primary-code distinction. This provides further evidence to suggest that types can be distinct even when the difference between them is less than eight points. While the descriptive statistics show a relation between primary-code distinction and congruence, other factors must also be considered. For example, the observed relation between primary-code distinction and
congruence may have occurred by chance alone. Also, even if a significant relation does exist, other variables may account for all of the variance in congruence that the researcher originally attributed to the variable primary-code distinction. In other words, other variables, such as consistency and profile elevation may affect congruence in a way that makes primary-code distinction irrelevant. The researcher decided to examine these variables using logistic regression, which allows one to see the relative impact of a predictor variable on a criterion variable, while controlling for other variables. The remaining hypotheses address these issues.

The second hypothesis stated that primary-code distinction relates positively to congruence between RIASEC type and expressed vocational interest. This means that increased numerical distinction between participants’ first two SDS codes increases the likelihood of finding a match between their primary inventoried type and the primary type associated with their first expressed vocational interest. The descriptive statistics reflect this by showing that congruence increases as primary-code distinction increases. However, an observed trend between two variables does not necessarily indicate a significant relation. Results from the logistic regression analysis helped to establish that a significant positive relation does exist between primary-code distinction and congruence, and that this relation cannot be accounted for by chance factors alone. Furthermore, this relation exists even after controlling for other variables that might affect congruence, such as consistency, and profile elevation. This means that the likelihood of finding a
match between participants’ inventoried and expressed vocational interests increases as their top two SDS codes become more distinct.

We would expect to observe this result because increased distinction between two types suggests participants resemble one type more than the other. For example, consider two participants with the following top two SDS scores, Participant 1: Social = 27, Conventional = 23, Participant 2: Social = 27, Conventional = 25. With a difference of four points between the top two SDS scores, the first participant demonstrates a more distinct profile than the second participant. Given this, we would expect the first participant to be more likely to state a Social type expressed vocational interest than the second participant.

The third hypothesis stated that consistency moderates the relation between primary-code distinction and congruence. Consistency refers to the similarity between the first two types in the RIASEC profile. Adding variables such as consistency to the logistic regression model allowed the researcher to isolate the relative effects of variables that, theoretically, might influence the outcome variable, i.e. congruence. The researcher included consistency in the logistic regression analysis because, theoretically, this variable might moderate the relation between primary-code distinction and congruence. A moderator variable affects the strength and direction of a relation between two other variables. This means that the relation between primary-code distinction and congruence may vary at different levels of consistency. For example, there may be a positive relation between primary-code distinction and congruence for participants who demonstrate high
consistency, while there may exist a negative relation between primary-code distinction and congruence for participants who demonstrate low consistency.

Results from the logistic regression showed no significant moderator effect for consistency, while examining the relation between primary-code distinction and congruence. This means that the relation between primary-code distinction and congruence did not change in strength, or direction, at the three levels of consistency. Therefore, the researcher concludes that consistency did not moderate the relation between primary-code distinction and congruence. Moderator variables that proved insignificant must also be analyzed for main effects. A main effect occurs when a significant linear relation exists between two variables. Results from the logistic regression show a significant main effect exists for consistency, where congruence increases as consistency increases. This means that, as participants’ vocational interests become more similar, the likelihood of finding a match between their primary inventoried type, and the primary type associated with their expressed choice, also increases. We would expect to observe this result because participants with high consistency do not have as many diverse competing vocational interests, and therefore tend to have an easier time making a vocational choice.

The research did not test the fourth hypothesis because of the strong correlation between differentiation and primary-code distinction. Logistic regression requires that predictor variables be independent of one another. The researcher excluded differentiation from the model because primary-code distinction represented the variable
of most interest. The fifth hypothesis stated that profile elevation moderates the relation between primary-code distinction and congruence. Profile elevation refers to the total sum of scores in a RIASEC profile, and indicates participants’ level of optimism. Participants with high profile elevation scores tend to be more social and energetic in exploring vocational choices, while participants with low profile elevation scores tend to be less social and more reserved in exploring vocational choices. The researcher included profile elevation as a moderator in the logistic regression model because, theoretically, profile elevation may moderate the relation between primary-code distinction and congruence. For example, there may exist a positive relation between primary-code distinction and congruence for participants who demonstrate high profile elevation scores, while there may exist a negative relation between primary-code distinction and congruence for participants who demonstrate low profile elevation scores. Results from the logistic regression showed no significant moderator effect for profile elevation, while examining the relation between primary-code distinction and congruence. This means that the relation between primary-code distinction and congruence does not change in strength, or direction, at varying levels of profile elevation. The researcher concludes that profile elevation does not moderate the relation between primary-code distinction and congruence. The logistic regression also showed that profile elevation had no significant main effect on congruence. This means that, profile elevation scores did not affect the likelihood of participants demonstrating a match between their inventoried type and the primary type associated with their first expressed vocational interest.
The descriptive statistics suggested certain RIASEC types were more likely to demonstrate congruence than other types. The researcher decided to run the logistic regression model again, this time adding RIASEC type as an independent variable. This post-hoc analysis showed significant main effects for primary-code distinction and RIASEC type. No significant main effects were found for Consistency or Sex. When we add RIASEC type to the model we must pick one type to compare all other types to. The researcher chose Social because it represented the largest number of participants in the dataset. Therefore, congruence for Social types was compared to congruence for all other types. The logistic regression showed that Social type participants were more likely to demonstrate congruence than Realistic, Conventional, and Enterprising participants. The greatest difference in congruence occurred between Social types, and Realistic, and Conventional types. We might expect to see this result because these participants attended a university that offers many Social type majors and few Realistic or Conventional type majors. Therefore Social participants may demonstrate greater congruence because they have more congruent choices available to them.

Practical Implications of Findings

The findings from the current study have practical implications for practitioners who administer the SDS. These findings aid practitioners by providing guidelines with which to interpret SDS profiles. Guidelines prove helpful, because they help direct exploration in a focused manner. The SDS advises users to explore every permutation of their three letter SDS summary code. This means that users should consider occupations
that match any one of six RIASEC summary scores. Although this prompts users to
explore occupations in breadth, it may also overload them with information, and confuse
them even further. Typically, students seek vocational guidance to identify a small set of
occupations to explore. They want to narrow this focus to exploration-in-depth, not
expand it to exploration-in-breadth. Advising users to interpret SDS results in this
manner ignores, not only the “rule of eight”, but also any difference between RIASEC
types. This means that the “rule of eight” is effectively ignored as a guideline for
interpreting SDS profiles.

Practitioners can use the findings of this study to more confidently determine the
primary RIASEC type in an SDS profile, and advise individuals accordingly.
Specifically, practitioners should not consider primary-code distinction scores that fall
below eight points as meaningless just because they fall within the SEM. Instead,
practitioners should consider primary-code distinction scores greater than, or equal to,
four points as indicative of a meaningful distinction between individuals’ top two
RIASEC types. Two case studies demonstrate the practical implications of these new
interpretative guidelines. Both case studies use RIASEC profile scores from participants
in the current study.

Case Study 1

Table 15 displays the SDS results for a female participant in the current study.
The results include the participant’s top four occupational daydreams, and three letter
SDS summary code, SCE, where Social = 27, Conventional = 23, Enterprising = 17. The
absolute difference between the top two inventoried types provides a measure of the individual’s primary-code distinction, which equals 4 points. Using the “rule of eight”, a practitioner would conclude that a difference of four points between the Social and Conventional types is not enough to distinguish the two. Consequently, the individual might be advised to place just as much emphasis on exploring Conventional occupations, as Social occupations. However, the findings from the current study suggest that the primary-code distinction of four points is a large enough difference to distinguish the two types, and conclude that the participant most resembles the Social type. This participant would be best advised to explore Social occupations before exploring Conventional occupations. The participant’s occupational daydreams provide support for this interpretation, given that the first three daydreams represent Social type occupations.
Table 15

SDS Results for Case Study 1

<table>
<thead>
<tr>
<th>Realistic</th>
<th>Investigative</th>
<th>Artistic</th>
<th>Social</th>
<th>Enterprising</th>
<th>Conventional</th>
</tr>
</thead>
<tbody>
<tr>
<td>13</td>
<td>8</td>
<td>14</td>
<td>27</td>
<td>17</td>
<td>23</td>
</tr>
</tbody>
</table>

Table 16

SDS Occupational Daydreams for Case Study 1

<table>
<thead>
<tr>
<th>Position</th>
<th>Occupational Daydream</th>
<th>SDS Type</th>
</tr>
</thead>
<tbody>
<tr>
<td>1&lt;sup&gt;st&lt;/sup&gt;</td>
<td>First grade teacher</td>
<td>Social</td>
</tr>
<tr>
<td>2&lt;sup&gt;nd&lt;/sup&gt;</td>
<td>Elementary Physical Education</td>
<td>Social</td>
</tr>
<tr>
<td>3&lt;sup&gt;rd&lt;/sup&gt;</td>
<td>School Counselor</td>
<td>Social</td>
</tr>
<tr>
<td>4&lt;sup&gt;th&lt;/sup&gt;</td>
<td>Business Administrator</td>
<td>Enterprising</td>
</tr>
</tbody>
</table>
Case Study 2

Table 17 displays the SDS results for a male participant in the current study. The results include the participant’s top four occupational daydreams, and three letter SDS summary code, ESC, where Enterprising = 46, Social = 42, Conventional = 31. Similar to the female participant in the first case study, this participant’s primary-code distinction score equals 4 points. Using the “rule of eight”, a practitioner would conclude that a difference of four points between the Enterprising and Social types is not enough to distinguish the two. Consequently, the individual might be advised to place just as much emphasis on exploring Social occupations, as Enterprising occupations. However, the findings from the current study suggest that the primary-code distinction of four points is a large enough to distinguish the two types, and conclude that the participant most resembles the Enterprising type. This participant would be best advised to explore Enterprising occupations before exploring Social occupations. The participant’s occupational daydreams provide support for this interpretation, given that all four daydreams represent Enterprising type occupations.
Table 17

SDS Results for Case Study 2

<table>
<thead>
<tr>
<th>Realistic</th>
<th>Investigative</th>
<th>Artistic</th>
<th>Social</th>
<th>Enterprising</th>
<th>Conventional</th>
</tr>
</thead>
<tbody>
<tr>
<td>17</td>
<td>9</td>
<td>10</td>
<td>42</td>
<td>46</td>
<td>31</td>
</tr>
</tbody>
</table>

Table 18

SDS Occupational Daydreams for Case Study 2

<table>
<thead>
<tr>
<th>Position</th>
<th>Occupational Daydream</th>
<th>SDS Type</th>
</tr>
</thead>
<tbody>
<tr>
<td>1\textsuperscript{st}</td>
<td>Attorney</td>
<td>Enterprising</td>
</tr>
<tr>
<td>2\textsuperscript{nd}</td>
<td>International businessman</td>
<td>Enterprising</td>
</tr>
<tr>
<td>3\textsuperscript{rd}</td>
<td>Salesman</td>
<td>Enterprising</td>
</tr>
<tr>
<td>4\textsuperscript{th}</td>
<td>Insurance manager</td>
<td>Enterprising</td>
</tr>
</tbody>
</table>
Limitations

Certain factors limit the results reported and conclusion drawn in the current study. The results of the study are delimited to exploratory freshman students attending a large liberal arts university. Therefore, these results are only generalizable to similar such populations. This study may also be delimited by the manner in which orientation instructors administered the SDS. Students completed the SDS as a take home assignment. There is no way for the researcher to know the conditions under which each participant completed the instrument. Some may have been more focused than others and paid more attention while filling out their responses. However, Holland designed the SDS as an intervention that could be self-administered and scored. Therefore, the researcher does not consider this issue to be a serious delimitation.

The study is also delimited by the nature of the concurrent design chosen by the researcher. This limited the researcher to performing a correlational analysis, which helps to show relations between variables, but cannot be used imply causation. The uneven distribution of RIASEC types for female participants highlights a factor that limits the results of the study. While the distribution of RIASEC types for male participants appeared even, female participants demonstrated a far greater tendency to resemble the Social type than any other type. The study is also limited due to the uneven distribution of male and female participants. The data collected included far more female participants (1497) than male participants (900).
Recommendations for Future Research

The current study represents a cross-sectional analysis of data, and examined congruence using two concurrent measures of vocational interest, SDS inventoried interests and SDS expressed vocational interests. Follow-up research should use longitudinal data to examine the ability of primary-code distinction, RIASEC type, and other theoretically derived variables, to predict congruence. This research is now possible because the dataset used in the current study included undergraduate students between 1996 and 2002, and many of these students have since graduated. Further research should examine participants’ graduating major, which can be typed using Holland’s RIASEC typology. Researchers can then compare this RIASEC type to the type associated with participants’ expressed vocational interest, and inventoried interest, using their original SDS results. The results of this research may help to determine the predictive validity of the SDS with exploratory students, while also examining the relative importance of primary-code distinction.

Researchers can improve on the current design by collecting data about participants’ first occupational choice after graduation. The occupations can be typed using Holland’s RIASEC typology, and then compared to participants’ original RIASEC type as derived from their SDS results. This improves upon the current design because it compares what the SDS predicted participants to choose with the occupation they actually chose. This research also helps to compare the relative predictive ability of expressed vocational interests and inventoried interests. To extend this research further,
researchers might also examine participants’ pattern of expressed vocational interests to see if participants who expressed vocational interests of the same type are more likely to choose an occupation of the same type.

Summary

This study examined Holland’s “rule of eight”, in an effort to develop and improve interpretative guidelines for the SDS. Results from descriptive statistics suggested a positive linear relation exists between primary-code distinction and congruence, such that congruence increases as primary-code distinction increases. The descriptive statistics also showed that many participants demonstrate congruence before primary-code distinction reaches eight points. A large number of participants demonstrated congruence when the distinction between their top two SDS types equaled only four points. Results from logistic regression confirm that a significant positive relation existed between primary-code distinction and congruence, and that this relation cannot be attributed to chance factors alone. The logistic regression model isolated the relative effect of primary-code distinction while controlling for the effects of other variables that might explain the variance in congruence, including: consistency, profile-elevation, and RIASEC type. Even after controlling for these variables, the logistic regression analysis showed that primary-code distinction helps to predict congruence. The results showed that a one point increase in primary-code distinction increased the likelihood of congruence by 8%. Certain RIASEC types demonstrate greater congruence than others, in particular Social and Investigative types. In conclusion, the researcher
advises practitioners to consider using the “guideline of four”, rather than “rule of eight”, when interpreting SDS profiles.
REFERENCES
REFERENCES


