The Validity of the Strong Interest Inventory in Predicting College Major Choice and Academic Achievement

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THE VALIDITY OF THE STRONG INTEREST INVENTORY IN PREDICTING COLLEGE MAJOR CHOICE AND ACADEMIC ACHIEVEMENT

Abstract

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The current study examines the Strong Interest Inventory's (SII) ability to measure vocational interests and better understand how it predicts concurrent undergraduate academic majors. Although much literature exists concerning vocational interest measurement, no published study has utilized all scales on the SII to predict concurrent academic majors while also exploring the extent of the congruence-achievement hypothesis on undergraduate students. Furthermore, no previous empirical investigations have explored the way classification hit rate percentages were calculated or identified the rank of the matched Occupational Scales (OSs) on the SII.

The concurrent validity of the SII was tested by (a) examining hit rates for the OSs in predicting college major choice utilizing the McArthur method (N = 100 females and 100 males); and (b) analyzing which scales (i.e., General Occupational Themes [GOTs], Basic Interest Scales [BISs], Personal Style Scales [PSSs]) on the SII are more effective at differentiating and predicting concurrent college majors (N=501). The congruence-achievement hypothesis was tested by quantifying the amount of congruence between participants' Holland personality types and the types associated with their declared academic majors, and how well this congruence predicts level of achievement (i.e., GPA).

Findings supported the ability of the SII to accurately predict concurrent majors at the undergraduate level. Specifically, the first hypothesis, which stated that the OSs of the SII will predict a participant's exact academic major (i.e., Direct Excellent Hit) for at least 35% of the sample, was supported. The second hypothesis, which predicted that the BISs of the SII will show the highest level of accuracy in predicting participant academic majors followed by the GOTs and PSSs, was also supported. Finally, the last hypothesis, which predicted that greater congruence between individuals' GOT scores and their academic majors will be associated with greater cumulative GPAs, was not supported. Strengths, limitations and future directions are discussed.

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Dedications

First and foremost this dissertation is dedicated to my mother. I literally would not have been able to do this without you. Your continued belief in me has helped me exceed my own expectations. I also want to dedicate this dissertation to those who work against the odds every day to make their dreams come true.

CHAPTER ONE

Introduction

Vocational interests, which have been investigated for nearly 100 years, represent one of the most studied areas within the field of counseling psychology. Nonetheless, many aspects of vocational interests warrant further exploration. This is clearly manifested in the February 2007 issue of the *Journal of Career Assessment*, which was dedicated to career interest testing over the past 30 years (Walsh, 2007).

One area of research that would benefit from further investigation is the way counselors and researchers assess vocational interests. Watkins, Campbell, and Nieberding (1994) surveyed 600 psychologists and found that the Strong Interest Inventory (SII) was the most commonly used vocational interest inventory. In an effort to have the most contemporary and precise instrument available to professionals, this inventory has been modified significantly since E.K. Strong Jr. initially created it over 80 years ago (Dik & Hansen, 2004; Donnay, Morris, Schaubhut, & Thompson 2004; Strong, 1927; Swanson & Gore, 2001). With so many significant modifications over time, research on the SII has been unable to keep pace. The concurrent validity of the SII was the central focus of this study. The SII is based upon Holland's theory.

Holland's Typological Theory

Holland's (1985) theory is one of the most widely studied career theories. It is also one of the most frequently used in practice because of its connection with the SII. Accordingly, it is important to review and clarify the defining features of Holland's theory because they will be referred to in some of the stability and validity studies that are subsequently reviewed.

John Holland attempted to create an empirically-rooted occupational trait-and-factor classification system, borne out of his work as a career counselor. His theory was considerably more comprehensive than other trait-and-factor theories during the late 1950s, as it accounted for an individual's career development across the lifespan, lifestyle interests (e.g., preferred learning environments, leisure activities, living environments), and occupational environments (Donnay et al., 2004). Holland's theory is rooted in a person-environment fit concept and integrates the six major factors that Guilford (1954) had identified in his comprehensive factor analysis of measures of interests (Holland, 1985). Holland attempted to clarify the nature of person and environmental fit by making reference to the concepts of calculus, consistency, differentiation, identity, and congruence (Swanson & Gore, 2001).

Holland's theory is based on four main assumptions (Holland, 1985): (a) individuals can be classified into six different types: Realistic (R), Investigative (I), Artistic (A), Social (S), Enterprising (E), and Conventional (C) (i.e., the RIASEC model); (b) environments can be classified into the same six categories; (c) individuals avoid environments that require them to perform activities they dislike and instead seek out environments that support and nurture their skills and abilities; and (d) individuals' work behaviors are dictated by the dynamic interaction between their personalities and the defining features of their work environment. Holland emphasized how influential this dynamic was in predicting an individual's job performance, satisfaction, and stability (Donnay et al., 2004).

The six individual types proposed by Holland (1985) have specific defining features that result from being immersed in "our culture" (Holland, 1985, p. 19). The

Realistic type is aligned with a preference for working with tools, objects, machines, and animals. These preferences increase the likelihood of advancing technical competencies relating to mechanical, agricultural, electrical, and manual labor. The Realistic type values physical ability, concrete things, and conformity. Individuals subscribing to this type are said to be inflexible, asocial, practical, and uninsightful. The Investigative type has a preference for activities that involve observational, symbolic, or systematic examination of physical, biological, or cultural events. These preferences typically result in advancing abilities in mathematics and sciences. This type of individual can be described as being curious, analytical, intellectual, and introspective. The Artistic type has a preference for activities that are unsystematic, involving the manipulation of physical or verbal entities in an effort to create artistic forms. Engagement in such activities advances competencies in language, art, music, drama, and writing. This type of individual can be described as emotional, expressive, imaginative, and nonconforming. The Social type is defined by a preference for interacting with others in an effort to inform, train, develop, treat, or enlighten. Such preferences advance competencies in verbal abilities and interpersonal relations. This type of individual is described as being gregarious, idealistic, empathic, and extroverted. The Enterprising type displays a preference for activities leading to economic gain and organizational goals. These preferences lead to developing strengths in leadership, interpersonal interactions, and persuasive abilities. This type is typically described as confident, domineering, extroverted, and energetic. The last type, Conventional, displays an affinity for activities that are systematic and orderly, involving the manipulation of data (written and numerical), record keeping, and filing materials. A preference for these activities advances clerical, computational, and business aptitudes. This type is frequently described as being efficient, practical, methodical, and unimaginative (Holland, 1985).

In an effort to graphically depict the RIASEC model, Holland placed the six interest types in the structural shape of a hexagon, which depicts the relative size of the correlations among the six types (Holland, Fritzche, & Powell, 1997). Thus, adjacent types have been shown to correlate more highly than types separated by one position or opposite types. This relates to the concept of calculus. Calculus refers to the spatial arrangement, between both the personality types and environments displayed on the hexagon. This arrangement aids in displaying the degree of theoretical relatedness between types and environments. For example, the Realistic and Social types display a lower level of theoretical relatedness due to being at opposite poles on the hexagon, as compared to the Conventional and Enterprising types, which fall next to each other on the hexagon (Holland, 1985).

Consistency refers to the manner in which the codes (subtypes) that comprise an individual's code type fall on the hexagon. Subtypes or codes that are next to each other on the hexagon (e.g., R and I) display a higher level of consistency or psychological similarity than those that are separated by other letters or that fall on opposite sides of the hexagon (e.g., A and C) (Swanson & Gore, 2001). Holland emphasized the importance of consistency in relation to success, stability, and persistence of vocational choice (Holland, 1985).

Differentiation refers to how some individuals or environments are noticeably more defined in terms of Holland's six types than others (Holland, 1985). Holland states that an individual may closely align with a single code type or an environment that is characterized and dominated by a single type. During interest testing, this would result in a profile with sharp peaks and low valleys. Qualitatively, this type of individual would have an affinity for particular tasks or activities. In contrast, some individuals or environments have poor differentiation and display similar levels of multiple types, resulting in a flat profile on interest inventories. These individuals have a wide range of interests and "would be characterized more by unpredictability than any other trait" (Holland, 1985, p. 26).

Holland's (1985) concept of identity refers to the lucidity and constancy of an individual's identity or the identity of an environment. He elaborates further, stating that individuals' goals, interests, and abilities represent their identity. Environmental identity is an organization's ability to set clearly defined goals, activities, and commensurate compensation over an extended period of time. Individuals with high identity have very specific and predictable vocational goals. In contrast, individuals with low identity have many nonspecific vocational goals and might be considered unpredictable in solving problems.

Holland (1985) also stated that individuals with certain interests or personalities will seek out corresponding and supporting career, educational, or recreational environments where they can express their personalities. Holland contended that, when this congruence between person and environment occurs, individuals retain higher levels of satisfaction and achievement in their chosen careers. Holland argued that the level of congruency is critical in predicting stability, satisfaction, and success within an individual's career. For example, when individuals have an Investigative personality/interest type, they will display the most congruence and satisfaction in

Investigative work environments (Holland, 1985). However, if they are placed in an enterprising work environment, they will display low congruence and satisfaction according to Holland's theory.

In chapter 2, I will address the theoretical underpinnings as well as the structure of the SII, clarify interest stability, and provide a history of the validity testing on the SII. I emphasize validity testing on the SII because investigation of other interest instruments has been comparatively sparse. My research could assist vocational counselors in better understanding the importance of validity testing with interest inventories and the ability of interest inventories to "predict" current and future academic and occupational pursuits. This would enhance service delivery to clients that remain undecided about their academic major. At an organizational level, this study could aid in increasing student retention rates at universities. Universities have identified career indecision as a growing concern and are allocating significant resources to address this issue. This study would contribute to this area of research by addressing questions that remain unanswered. The research questions are: (a) How well does the SII differentiate between different college majors? (b) What scales (i.e., GOTs, BISs, OSs and PSSs) on the SII provide the most accurate prediction of concurrent college majors? (c) What effect does congruence between an individual's SII results and academic major play with respect to academic performance?

CHAPTER TWO

Literature Review

The purpose of the present study is to assess the ability of the SII to concurrently "predict" academic majors and academic achievement at the undergraduate level. The initial section addresses interest inventories commonly used by practitioners and researchers. The next section provides a brief overview of methods researchers have used to assess interest stability over time. The primary focus of this literature review is how validity testing on the SII has developed over the past 60 years. In addition to the SII, three other commonly used interest inventories are noted in this section for comparison purposes. To enhance clarity, this section was broken down into six different categories based upon criterion (i.e., occupational, academic choice) and type of validity (i.e., predictive, concurrent). This chapter ends with an overview of the present study and the hypotheses to be tested.

Commonly Used Interest Inventories

Numerous interest inventories have emerged over the past 60 years, enabling individuals to ascertain a connection between interests and specific vocational and academic career paths. The four most popular interest inventories include the Strong Interest Inventory (SII), Self-Directed Search (SDS), the Campbell Interest and Skill Survey (CISS), and the Kuder Occupational Interest Survey (KOIS), which can all be related to Holland's RIASEC typology (Lent & Brown, 2005).

Strong Interest Inventory (SII)

The Strong Interest Inventory is one of the oldest measures still in use. It was introduced over 80 years ago and remains one of the most thoroughly researched and widely used assessments (Watkins et al., 1994). It was initially titled the Strong Vocational Interest Blank (SVIB; Strong, 1935). Subsequently, the SII has been revised several times with the most recent revision in 2005. The power of the SII is based on two assumptions: (a) the activities in which individuals engage at their jobs reflect their preferred interests; and (b) individuals who respond to items in a similar fashion have similar interests, and will be satisfied in the associated occupations (Donnay et al., 2004).

General occupational themes. General Occupational Themes (GOTs) represent the broadest category of scales on the SII and reflect a client's overall interest orientation. Each GOT score is interpreted in terms of typical work activities, potential competencies, self-concept and values, environments, and typical hobbies. GOTs play a significant role in the theoretical organization of the SII. GOTs were first included in the 1974 version of the SII, and are rooted in Holland's person-environment theory, specifically the six person-environment categories (i.e., RIASEC). An occupation is classified into a given theme code based upon the requirements of that occupation (Donnay et al., 2004).

Only minor changes were made to the GOTs during the most recent revision. These revisions focused on broadening certain categories to be more inclusive of recent advancements in technology (e.g., computers). The Conventional theme code has been reworked to include careers relating to programming and working with computer software. The Realistic theme now includes working with computer hardware. The manual states that these additions have not conceptually affected these themes. The SII manual reports test-retest reliability estimates for the GOTs ranging from .80 to .92 over a 2 to 23 month time period. To establish validity, the manual refers to the GOTs median correlation of .77 across the six themes with the corresponding scales on the Vocational Preference Inventory, which is also based upon Holland's RIASEC typology.

Basic interest scales. The Basic Interest Scales (BISs) were first introduced in the SII in the late 1960s, and have also been revised considerably since that time. The main purpose of the 30 BISs is to enhance the information provided by the GOTs and Occupational Scales (OSs). For example, the Artistic GOT includes BISs for visual arts and design, performing arts, culinary arts, writing, and mass communication. Technically, the BISs are not GOT subscales, but they do contain specific aspects that are conceptually and psychometrically similar to the GOTs. Each GOT is defined by four to six BISs. The BISs are homogenous scales, as items that correlate with one another and measure related content are grouped together. The SII manual reports test-retest reliability estimates for the BISs ranging from .74 to .93 over a 2 to 23 month time period. The manual reports concurrent validity estimates for occupational group membership for the BISs ranging from 21.76% to 24.4%, however predictive validity estimates were not provided (Donnay et al., 2004).

Occupational scales. The Occupational Scales (OSs) comprise the oldest portion of the SII and provide the most precise information related to occupational opportunities. The SII has 244 OSs, 122 for females and 122 for males. The OSs were created with the intention of asking, "Does the respondent have likes and dislikes similar to women or men in this occupation?" (Donnay et al., 2004, p. 103). Conceptually, this allows examinees to compare their interests to individuals from 122 different occupations. The OSs are comprised of items that differentiate all individuals in specific occupations from men or women in general. The SII manual reports test-retest reliability estimates for the

OSs ranging from .71 to .93 over a 2 to 23 month time period. The manual reports validity estimates from the studies that will be covered below (Donnay et al., 2004).

Personal style scales. The Personal Style Scales (PSSs) were first introduced in the 1994 version of the SII. The PSSs were constructed to attain a more lucid understanding of the individual's preferences for learning or work in general. The five Personal Style Scales help to define an individual's preference for work style, learning environment, leadership style, risk taking, and team orientation (Donnay et al., 2004).

The Work Style Scale differentiates individuals who prefer working with people from those who prefer working with ideas, data, and things. The Learning Environment Scale differentiates individuals who display a preference for learning in a traditional academic environment from those who prefer to learn in more practical settings. The Leadership Scale differentiates individuals who prefer to direct others from individuals who prefer to lead by example. These individuals have a preference for directing others and display strengths for taking the initiative and utilizing their verbal abilities to persuade others around them. The Risk Taking Scale differentiates individuals who prefer taking less risk from those who are more likely to take chances. This scale was developed to encompass both physical (e.g., adventure) and general risk-taking interests (e.g., financial). The most recent scale is the Team Orientation Scale. This scale differentiates individuals who display a propensity for working independently from those who prefer to work in groups toward a common goal. The SII manual reported internal consistency estimates ranging between .82 and .87.

Self-Directed Search

Over 30 years ago, John Holland developed the Self-Directed Search (SDS; Holland, Fritzche, & Powell, 1997), which has undergone three different revisions since its inception. The most current revision occurred in 1994. This latest version is composed of 228 items. The SDS aspires to be one of the most user-friendly instruments, as it can be self-administered, self-scored, and self-interpreted. The SDS is theoretically grounded in Holland's RIASEC typology, subscribing to the concepts of person-environment fit, congruence, consistency, and differentiation. The test is broken down into six different sections: Occupational Daydreams, Activities Scales, Competencies Scales, Occupations Scales, Self-Estimates, and Summary Code Section. The technical manual reports Kuder-Richardson Formula 20 (KR-20) coefficients that range from .72 to .92 for the Activities, Competencies, and Occupational scales. KR-20 estimates for the Self-Estimate scales ranged from .37-.84. The summary score displays a higher and narrower range of reliability estimates (.90–. 92). Test-retest correlations occurring over a four- to twelve-week period ranged from .76-.89.

The Campbell Interest and Skill Survey

The Campbell Interest and Skill Survey (CISS) is comprised of 200 questions that assess vocational interests and 120 questions that assess self-estimated abilities, which are measured by a six-point Likert scale. Vocational interests are placed into seven general orientations: Influencing, Organizing, Helping, Creating, Analyzing, Producing, and Adventuring. These orientations are similar to Holland's RIASEC code types (or the SII General Occupational Themes), with the addition of the Adventuring orientation on the CISS. Validity studies have frequently compared the CISS to the SII, and therefore it is important to address the common elements these two interest inventories share (Campbell, Hyne, & Nilsen, 1992; Hansen & Neuman, 1999).

The Adventuring orientation on the CISS shares features with Holland's Realistic code type; both reflect an interest in physical activities. The CISS Producing category also resembles the Realistic type as it involves practical activities that typically require working with objects or machines. The CISS Influencing orientation corresponds to Holland's Enterprising type and includes occupations in which people influence, manage, and persuade others. The Organizing orientation in the CISS resembles Holland's Conventional type and involves activities that require following through with the instruction of others, planning, and working with data. The CISS Helping orientation is similar to Holland's Social type as it involves a significant engagement with others, strong interpersonal skills, and genuine concern for the well-being of other people. The Creating orientation in the CISS is analogous to Holland's Artistic type and emphasizes unstructured and creative activities such as acting, writing, and musical performances. Lastly, the CISS Analyzing orientation resembles Holland's Investigative type and involves activities in which individuals observe, analyze, and solve problems (Campbell, Hyne, & Nilsen, 1992; Donnay et al., 2004).

Organized within the major orientation scales of the CISS is the assessment of interests and skills in tandem represented by the following scales: Basic Interest/Skill, Occupational Interest/Skill, and Special scales. The content of the 29 Basic Interest/Skill scales are analogous to the Basic Interest Scales (BISs) on the SII, but also include the following additional interests/skills: advertising/marketing, financial services, adult development, child development, international activities, fashion, woodworking, and animal care. However, the CISS fails to include the areas of data management and computer activities, thus showing its age. Alpha coefficients range from .69 to .92 for the Basic Interest Scales, and from .62 to .87 for the Skill Scales. Over a three-month period, test-retest reliability coefficients were displayed at .83 for the Interest Scales and .79 for the Skill Scales (Campbell, Hyne, & Nilsen, 1992).

The content of the 58 Occupational Skills scales in the CISS also resemble the Occupational Scales found in the SII, but differ in the way they were constructed. In developing the Occupational Skills scales on the CISS, both genders comprised the criterion (i.e., occupation) and contrast samples. In contrast, separate criterion (i.e., occupation) and contrast samples were used for each gender for the SII (Hansen et al., 2004).

The other CISS Special scales include Academic Focus (AF) and the Extraversion Scales (ES). The AF scales were constructed by utilizing contrast groups (i.e., individuals with low education contrasted to individuals with high education) and are broken down into two different scales that measure both an individual's academic interests and his or her self-perceived abilities. Over a three-month period, these two scales have shown test-retest coefficients of .87 and .77, respectfully. The ES is also broken down into two different scales, which relate to an individual's interest and skills related to social interactions in an office setting. These two scales have test-retest coefficients of .85 and .82, respectively (Campbell, Hyne, & Nilsen, 1992).

Kuder Occupational Interest Survey

The Kuder Occupational Interest Survey (KOIS) dates back to its first publication in 1941. It has a very colorful history, including its use by the armed forces during WWII. Like the SII, it has had several different names over the past 60 years. It was initially referred to as the Kuder Preference Record. Subsequently, it has been referred to as the Kuder General Interest Survey (KGIS), Kuder Occupational Interest Survey (KOIS), and, most recently, the Kuder Career Search with Person Match (KCSPM). This paper focuses on the KOIS, because no published validity studies have yet been identified for the KCSPM. The KOIS contains 100 items or sets, each listing three different activities. The respondent ranks the activities in each set, from most to least preferred. This results in the creation of an interest profile containing ten Vocational Interest Estimates (VIEs). Scores are reported as percentiles within the specific areas of Scientific, Artistic, Literary, Social Service, Musical, Outdoor, Computational, Clerical, Persuasive, and Mechanical. The ten VIEs can be converted into Holland's RIASEC types. Over a two-week period, the VIEs have displayed median test-retest correlations of .80. The KOIS also contains 109 Occupational Scales and 40 College Major Scales, with scores reported as lambda coefficients that indicate how well an individual's responses resemble the criterion group for each occupation and college major. These scales have displayed a median test-retest reliability of .90 (Diamond & Zytowski, 2000).

Career Interest Stability

Interest stability is a critical element that needs to be addressed when discussing the validity of interest tests. If interests display different levels of stability during different developmental periods, this could greatly impact the results of validity testing with an instrument. Low and Rounds (2007) put forth five different ways to conceptualize the stability of interests: (a) rank-order stability; (b) profile stability; (c) mean-level stability; (d) structural stability; and (e) congruence.

Researchers concerned with interest stability over time frequently investigate rank-order stability. It refers to stability versus change in the relative placement of individuals within a group for a particular interest at two or more points in time. For example, scores for each Occupational Scale of the SII can be correlated between two time periods (e.g., at the end of high school and at college graduation). Higher correlations indicate that individuals tend to retain their rank-order on a particular Occupational Scale over time. E. K. Strong (1951) conducted one of the first studies to investigate rank-order stability of the 34 areas that comprised the OS over a 22-year period. Correlation coefficients averaged .84 over five years, .82 over ten years, and .75 over twenty-two years. He further concluded that the age of the individual at initial testing and the length of time between test and retest affected rank-order stability. A meta-analysis conducted by Low, Yoon, Roberts, and Rounds (2005) reviewed 66 studies and indicated a trend of rank-order stability increasing as a function of age. This trend begins in adolescence, increases significantly, and peaks during early adulthood (i.e., 25–30 years of age), after which time it decreases slightly. Typical correlations ranged from .55 (12–14 year old group) to .83 (25–30 year old group) over a seven-year period. This method of interest stability investigation is not frequently utilized in contemporary validity testing research.

Profile stability is somewhat similar to rank-order stability, but includes multiple data points or scales that yield an overall interest profile for each individual at two or more points in time. Although Low et al. (2005) failed to report specific correlations across different time periods, the average of all studies reviewed indicated higher correlations than those found for rank-order stability (.70 versus .60, respectively). Overall, these results clearly display how interests become increasing more stable as a function of maturation during late adolescence, continuing through middle adulthood (i.e., 40 years old).

Mean-level stability refers to changes in average interest scores for individuals or groups over time. This type of stability is most commonly affected by historical events and maturation. It is very common for mean scores on interest scales to increase from the ages of 16 to 20 as individuals' desire for adult experiences increases (Low & Rounds, 2007).

Researchers have developed three quantitative methods to study structural stability: Correspondence Index (CI), Circular Unidimensional Scaling (CUS), and longitudinal structural equation modeling. Researchers developed these methods in an effort to quantify how well an individual's type score corresponds to the circular arrangement of the RIASEC typology. These scores are then correlated over time to reveal structural stability. Tracy and Ward (1998) created an inventory to measure children's interests and their perceived competency utilizing a RIASEC framework. Their results showed that there are differences in the RIASEC structure by age (i.e., elementary, middle school, and college). Furthermore, their results revealed an increase of fit to the circular RIASEC model as a function of maturation. Some evidence shows that the interest maturation process can begin as early as four years of age and is rooted in careers with strong ties to traditional male and female gender roles (Trice & Rush, 1995). Most research on interest stability has been conducted with adolescents and young adults, primarily due to convenience sampling (Low & Rounds, 2007). Similar to the previously mentioned findings, interest structures in adolescents adhere to the circular structure of Holland's RIASEC typology. It also appears that this adherence increases as a function of maturation from early through middle to late adolescence (Low & Rounds, 2007).

The last approach used to assess interest stability relates to the level of congruence present between individuals and their work environments. Researchers have developed complex algorithms to quantify congruence or the level of fit present between an individual's interest inventory results and their work environment (Low & Rounds, 2007). Arguably, this type of "stability" is better viewed as a type of predictive or concurrent validity, which is addressed in subsequent sections of this paper.

Validity Studies

Interest Tests and Occupational Choice

Predictive validity. To demonstrate the effectiveness of interest inventories, researchers test their predictive and concurrent validity. The ability of interest inventories to predict occupational choices is one of the hallmarks of these instruments. E. K. Strong was one of the first researchers to test the predictive validity of a vocational interest inventory. Strong (1935) tested the stability and validity of the Strong Vocational Interest Blank (SVIB) test scores with four propositions: (a) "men continuing in an occupation obtain a higher interest score in it than in any other occupation," (b) "men continuing in an occupation obtain a higher interest score in it than men entering some other occupation," (c) "men continuing in an occupation obtain higher scores in it than men who change from that occupation to some other," and (d) "men changing from other occupations to occupation X score higher in X prior to the change than they did in other occupations" (p. 335). These propositions were applied to SVIB data collected from 223 college seniors at Stanford University in 1927 (Time 1) and in 1932, five years after graduation (Time 2). Results showed significant support for the first two propositions. Some support was shown for the third proposition, but only three occupational comparisons were possible, making it a tenuous relationship at best. The fourth proposition was less clearly supported than the others.

In addition to these propositions, this study addressed the question: "To what extent do college graduates maintain the occupational plan they had as seniors in college?" (p. 332). Results showed that more than half of all participants changed their occupational choice five years after graduating. Strong delineated these results further, indicating that 9% had made only a "slight change," 22% had made what he considered to be a "significant change," and 21% had changed from undecided to a "specific choice." It is important that these results be viewed in the historical context in which they occurred. This was a time period marked by extreme economic hardship. Most participants that had changed their occupational "choice" did so to maintain employment.

This study was important because it represented the first attempt to establish the validity of an interest inventory. This study influenced future investigations in many ways. Specifically, it illustrated the inherent complexity of the classifications made in matching test results to participant occupations. In this regard, Strong (1935) stated that, "in view of the great complexity of the data it is improbable that any two persons would exactly agree upon the proper grouping, or even that the writer could exactly duplicate the present grouping on another occasion" (p. 332). This calls into question one of the central tenets of scientific methodology--replication, which has not been frequently addressed by researchers.

Another central issue precipitated by Strong's original work was the question of what should serve as the criterion during validity testing. Strong (1935) made reference to the final vocational choice as the ultimate criterion. However, as he pointed out, how do we know when an individual has reached their final vocational destination? Strong contended that the "ultimate criterion" was not plausible, nor was a perfect correlation possible between one's interest test results and his or her occupation. Although a perfect correlation is not likely, Strong contended that a higher degree of correlation should be present in college graduates, as compared to less educated individuals because the former have had the opportunity to select their careers (Strong, 1935). Strong believed that the best way to validate a vocational interest test was to determine if scores could differentiate individuals who are "satisfactorily adjusted" in an occupation from those who are not.

Strong (1951) conducted a follow-up investigation in 1949. This study utilized two groups of participants, who differed in their test administration date. The first group was the original 1927 sample, whereas the second group consisted of the 1930 incoming class of freshman at Stanford University. Both groups were then re-administered the SVIB in 1949. In the first group, 132 participants did not change occupations, while 86 participants did change. The second group displayed similar results, with 128 participants not changing occupations and 94 showing some degree of change. Overall, both groups displayed less change than was present in Strong's original study (1935); 60% of participants remained in their occupations over this time period. For both groups, OS scores for the scales associated with their occupations increased significantly over time. The average of the first group increased from 45.4 to 46.7. The second group averaged lower at the initial administration (43.6) than the first group, but displayed a greater increase in scores over time (47.0). Unfortunately, this investigation failed to include the specific degree of occupational change as in the previous study (Strong, 1935). Interestingly enough, this article also failed to mention or compare the data provided in the 1935 study. The major shortcomings of these two studies was a failure to provide specific hit rates quantifying how well participants' interest inventory results matched their occupations.

This shortcoming was first recognized by McArthur (1954), who was the first researcher other than Strong to conduct predictive validity studies with the SVIB. This was a seminal paper in many ways, setting a standard for validity testing for more than 30 years. Subsequently, many validity studies have utilized the McArthur method (Dolliver et al., 1972; Hansen & Dik, 2004; Hansen & Swanson, 1983; Hansen & Tan, 1992; Spokane, 1979; Worthington & Dolliver, 1977). McArthur's research tested Strong's (1935) initial four propositions regarding the validity of the SVIB. Strong used these four propositions to examine the validity of the SVIB, but failed to provide percentages of individual's for whom the propositions were true, and did not report how many individuals actually entered and remained in the occupations that were suggested by their SVIB results.

McArthur’s 14-year longitudinal study, which ran from 1939 to 1953, included 61 male participants enrolled at Harvard College during their sophomore year in 1939. Interpretive results of testing were not provided to the participants, as the tests were not scored until 1953. McArthur compared the participants’ job titles in 1953, with the SVIB scale that fell nearest to their job title. He remarked that, for one participant, there was no commensurate title on the SVIB for economist, and he matched the occupation with the SVIB office man scale. McArthur acknowledged that doing so required “mildly subjective evaluations by the investigator” (p. 346). There was no further explanation regarding how this significant process was conducted, and the table describing the specific matches made between a participant’s job title and the corresponding SVIB scale was not provided in the original article.

One of the most significant contributions of McArthur’s work was his effort to create explicit terminology, which had been implicit in Strong’s (1935, 1951) original work. In McArthur’s terms, a “good hit” was present when an individual’s current occupation matched one of their three highest OS scores (considered “A” scores) on the SVIB. An “A score” is represented by an OS T-score of greater than 45 (Strong, 1951). In contrast, “B+” OS scores (i.e., quartile scores between –1 and –2) were treated as “poor hits.” Strong (1935) had previously defined all “B scores” as being “intermediate, meaning he probably has those interests, but one can not be so sure of it as in the case of the A rating” (p. 335). Scores falling below B were considered a “clean miss.” McArthur also distinguished “direct” from “indirect” matches between an individual’s occupation and an OS score. “Direct” matches involved exact correspondence between occupations and an OS score on the SVIB (e.g., engineer). “Indirect” hits were more subjective and required an inference by the researcher, as in the example when McArthur concluded that an economist and office man held similar or commensurate interests. This approach differed from Strong's (1951), as Strong omitted data he could not match with a corresponding Occupational Scale.

McArthur (1954) concluded that Strong's second and third propositions (i.e., b and c) were largely supported by his findings. Thus, individuals in a given occupation were more likely to score high on the associated OS than individuals who were not in that occupation. Also, individuals who changed occupations were more likely to have a low score on the associated OS than those who were committed to that occupation. Other studies that have used the McArthur method have included the percentages of hits and misses. However, McArthur only provided raw frequencies in his study. In an effort to enhance interpretability across studies, I have calculated and provided the percentages, which can be found in Table 1.

McArthur derived other interesting findings. He concluded that individuals subscribing to occupations in engineering, theology, and education are highly predictable compared to individuals who owned their own businesses, whose occupations could not be accurately predicted from the SVIB. He further concluded that the central factor moderating the test's predictive validity was the seriousness of individuals in following their interests. In an effort to differentiate this possible moderating factor, he placed participants into two categories, those who attended public schools and those who attended private preparatory institutions. For those who attended public schools, the SVIB provided a "direct hit" 75% of the time, whereas the "direct hit" rate was 40% for

Table 1

Recalculated hit rate results (N, percentage) for concurrent and predictive validity studies concerning occupational choice using the Strong Interest Inventory

Study	**Validity**	**Direct**		**Indirect**		**Total**	
		N	**%**	**N**	**%**	**N**	**%**
Mc Arthur (1954)							
1939 SVIB Admin (N=60)	Good Hits	22	37.0	5	8.0	27	45.0
	Poor Hits	7	12.0	5	8.0	12	20.0
	Clean Misses	14	23.0	7	12.0	21	35.0
	Total	43	72.0	17	28.0	[a]	
Dolliver et al. (1972)							
Predictive Validity	Good Hits	45	35.0	9	7.0	54	42.0
1957 SVIB Admin (N=130)	Poor Hits	15	11.0	1	1.0	16	12.0
	Clean Misses	43	33.0	17	13.0	60	46.0
	Total	103	79.0	27	21.0		
Concurrent Validity	Good Hits	34	35.0	7	7.0	41	42.0
1969 SVIB Admin (N=98)	Poor Hits	10	10.0	2	2.0	12	12.0
	Clean Misses	40	41.0	5	5.0	45	46.0
	Total	84	86.0	14	14.0		
Worthington & Dolliver (1977)							
Predictive Validity	Good Hits	27	32.0	5	6.0	32	38.0
12-year time span SVIB (N=84)	Poor Hits	13	16.0	1	1.0	14	17.0
	Clean Misses	27	32.0	11	13.0	38	45.0
	Total	67	80.0	17	20.0		
Predicative Validity	Good Hits	27	22.0	17	14.0	44	36.0
18-year time span SVIB (N=125)	Poor Hits	13	10.0	4	3.0	17	13.0
	Clean Misses	36	29.0	28	22.0	64	51.0
	Total	76	61.0	49	39.0		

Study	Validity	Direct		Indirect		Total	
		N	%	N	%	N	%
Worthington & Dolliver (1977)							
Concurrent Validity	Good Hits	21	36.0	3	5.0	24	41.0
1969 SCII Admin (N=59)	Poor Hits	6	10.0	2	3.0	8	13.0
	Clean Misses	24	41.0	3	5.0	27	46.0
	Total	51	87.0	8	13.0		
Concurrent Validity	Good Hits	30	35.0	19	22.0	49	58.0
1975 SCII Admin (N=85)	Poor Hits	4	5.0	3	4.0	7	9.0
	Clean Misses	21	25.0	8	9.0	29	34.0
	Total	55	65.0	30	35.0		
Spokane (1979)							
Predictive Validity SCII	Good Hits	51	33.5	7	4.6	58	37.9
Females (N=152)	Poor Hits	20	13.1	6	3.9	26	17.0
	Clean Misses	49	32.2	20	13.1	69	45.1
	Total	119	78.8	33	21.6		
Predictive Validity SCII	Good Hits	140	45.3	16	5.1	156	50.4
Males (N=308)	Poor Hits	28	9.0	6	1.9	34	10.9
	Clean Misses	68	22.0	51	16.5	119	38.5
	Total	236	76.3	73	23.5		
Concurrent Validity SCII	Good Hits	69	45.3	9	5.9	78	51.2
Females (N=152)	Poor Hits	24	15.7	2	1.3	26	17.0
	Clean Misses	26	17.1	22	14.4	48	31.5
	Total	119	78.1	33	21.6		
Concurrent Validity SCII	Good Hits	151	49.0	26	8.4	177	57.4
Males (N=308)	Poor Hits	53	17.2	41	13.3	94	30.5
	Clean Misses	32	10.3	5	1.6	37	12.0
	Total	236	76.5	72	23.3		

Study	Validity	Direct		Indirect		Total	
		N	%	N	%	N	%
Hansen & Dik (2005)							
12-year Predictive Validity SII	Excellent Hits	48	32.5	21	14.2	69	46.6
Females (N=148)	Moderate Hits	13	8.8	8	5.4	21	14.2
	Poor Hits	43	29.0	15	10.1	58	39.1
	Total	104	70.3	44	29.7		
12-year Predictive Validity SII	Excellent Hits	30	33.3	8	8.6	38	41.9
Males (N=93)	Moderate Hits	8	8.6	4	2.3	12	10.9
	Poor Hits	35	37.6	8	8.6	43	46.2
	Total	73	79.5	20	19.5		
12-year Predictive Validity SII	Excellent Hits	78	32.3	29	12.0	107	44.4
Combined gender (N=241)	Moderate Hits	21	8.7	12	4.9	33	13.7
	Poor Hits	78	32.3	23	9.5	101	41.9
	Total	177	73.3	64	26.4		
Concurrent Validity SII	Excellent Hits	62	41.8	28	18.9	90	60.7
Females (N=148)	Moderate Hits	16	10.8	8	5.4	24	16.2
	Poor Hits	26	17.5	8	5.4	24	23.0
	Total	104	70.1	44	29.7		
Concurrent Validity SII	Excellent Hits	44	47.3	13	13.9	57	61.2
Males (N=93)	Moderate Hits	9	9.6	4	4.3	13	13.9
	Poor Hits	20	21.5	3	3.2	23	24.7
	Total	73	78.4	20	21.4		
Concurrent Validity SII	Excellent Hits	106	43.9	41	17.0	147	60.9
Combined Gender (N=241)	Moderate Hits	25	10.3	12	4.9	37	15.4
	Poor Hits	46	19.0	11	4.5	57	23.7
	Total	177	73.2	64	26.4		

those from private schools. Overall, these validity estimates were slightly lower than those in Strong's (1951) follow-up study.

McArthur's contemporaries indicated one major criticism of his study: replicating it was difficult (Stephenson, 1961). This was primarily due to the subjective nature of the "indirect hit" classifications. Although McArthur acknowledged this subjectivity, he did not describe how he made these indirect classifications. In a later article, Zytowski (1976) contended that McArthur made these indirect classifications by only viewing an individual's OS score (rather than the entire profile) and matching it (indirectly) to their occupation.

Dolliver, Irvin, and Bigley (1972) conducted a 12-year follow-up study that investigated the predictive validity of the SVIB. This study also addressed the inherent difficulty that researchers face when attempting to match an individual's present occupation to an appropriate OS on the SVIB. Dolliver et al. referred to a validity study conducted by Strong (1955), in which only 663 of his initial 884 participants were considered to have a directly corresponding OS. The method that Strong used was to average scores on two OS scores to match the participant's occupation. Strong conceded that this method was imprecise.

To circumvent this shortcoming, Dolliver et al. (1972) employed two different methods to achieve more accurate validity estimates, the McArthur method and a counseling test-interpretation framework. The detail provided by Dolliver et al. (1972) for the counseling test-interpretation method allows for its replication. The process involves working individually with clients and asking them a series of questions about how their SVIB results fit with their present occupation.

The major differences between this method and the McArthur method are the following: (a) all participants are utilized, (b) participants are able to provide a description of their present job in terms that relate to the SVIB scales, (c) several occupational scores are possible, and (d) broader categories are possible as participants rank-order the SVIB occupations that are most descriptive of their current occupation (Dolliver et al., 1972). Instead of classifying the results according to the McArthur procedure (i.e., good, poor, direct, indirect), researchers used the three categories of *helpful*, of *some use*, and *misleading* to qualify the match between an individual's OS score and present occupation. The *helpful* category included participants for whom one of their top five OS scores were "extremely descriptive of their present job." This category denotes participants whose test results would be of significant help in defining a clear occupational path. This category included 43% of all participants in the first administration or predictive condition. The *some use* category included participants for whom one of their OS scores ranked from six to ten were considered to be of "some use" in helping them select their present occupation. This category encompassed 29% of participants. The last category included participants who displayed OS scores ranked greater than ten. These results were considered unhelpful or "misleading" in selecting their present occupation. This category yielded 28% of participants (Dolliver et al., 1972).

In contrast to the counseling-interpretation method, the McArthur method resulted in the omission of 90 participants due to an inability to supply an accurate corresponding occupation with those presented on the SVIB. Specific predictive validity results for the McArthur method can be found in Table 1. Overall, results showed agreement between the two different methods employed. For example, the “good hit” condition was similar to those attained for the “helpful” category in the counseling-interpretation method (42% versus 43%, respectively).

Worthington and Dolliver (1977) conducted a follow-up investigation to the Dolliver et al. (1972) study in an effort to further examine the 12- and 18-year predictive validity of the SVIB. This study also sets itself apart in its re-examination of the occupational classifications provided to participants in the previous study (Dolliver et al., 1972) utilizing the McArthur method. These initial classifications were assessed for changes that might have occurred due to changing jobs, job titles, entering a new occupation, or attaining a different standard score on the two tests. This study advanced objectivity by linking the language found in the SCII manual (excellent hits, moderate hits, and poor hits) with those provided by McArthur (good hits, poor hits, and clean miss). These researchers also investigated the relationship between reported job satisfaction and standard scores on the SCII (Worthington & Dolliver, 1977).

In the 12-year (1957–1969) predictive validity study of the SVIB, there were 32% “direct good hits” and 6% “indirect good hits” (see Table 1). Only data from 84 participants were analyzed, as 57 participants were unable to be supplied with an appropriate and accurate occupational classification (Worthington & Dolliver, 1977). For the 18-year time period, there were less “direct good hits” (i.e., 22%) than for the 12-year time period, whereas “indirect good hits” were higher (i.e., 14%) than the previous period. Overall, the good or poor “direct hit” categories accounted for less of the total sample (32% versus 48%) over the 18-year time period than the 12-year period. Results such as these could indicate that the SVIB is less predictive over longer time intervals.

However, this data could also be indicative of results regressing toward the mean as the 18-year time period involved a significantly larger sample with only 16 participants disregarded due to classification difficulties (Worthington & Dolliver, 1977).

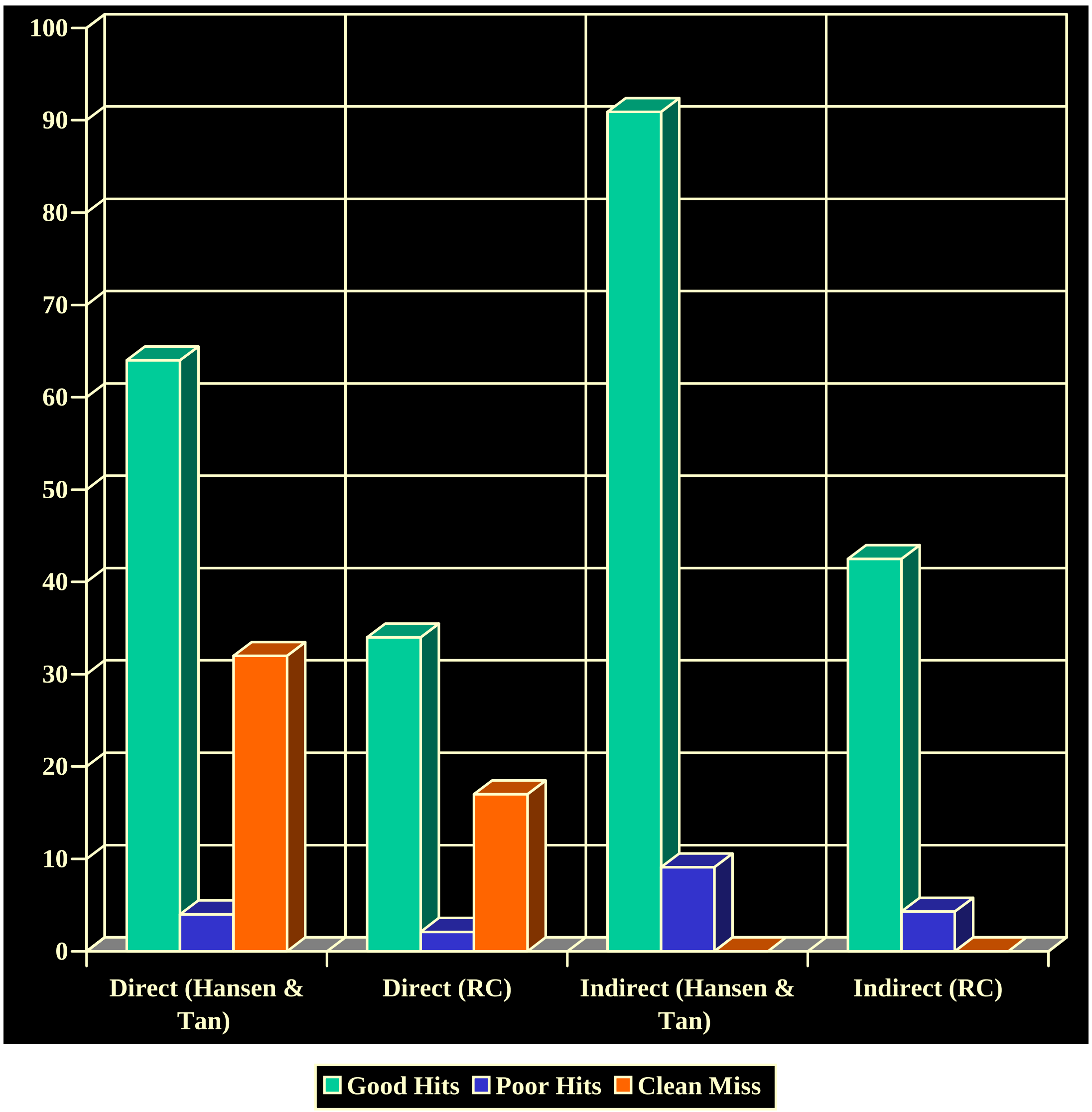
Results regarding the reliability of the McArthur classification method over time were assessed using specific criteria in five different categories: (a) classification, (b) job change, (c) job title change, (d) new occupation, and (e) score change. This method resulted in over one-third (34%) of participants receiving a different classification (i.e., direct good hit, indirect good hit, etc.) in the 12-year and 18-year investigations. Only 39% of participants were categorized identically in the 12-year and 18-year investigations. These findings underscore Strong's (1951) original premise denoting the complexity involved when researchers attempt to assign an appropriate occupational classification (Worthington & Dolliver, 1977).

Before presenting the results for Spokane's (1979) study and the subsequent studies summarized in Tables 1 and 2, it is important to note that the percentages shown in my tables for these studies are not those reported by the original authors. All of the McArthur-method studies conducted since 1979 employed a different method to calculate hit rates (i.e., Hansen & Dik, 2005; Hansen & Swanson, 1983; Hansen & Lee, 2007; Hansen & Neuman, 1999). This method yielded inflated and potentially misleading results. Figure 1 illustrates how this method of calculation inflates results. As a result of this method, Spokane (1979) and his contemporaries published results that were significantly superior to those studies conducted previously (Dolliver et al., 1972; McArthur, 1954; Worthington & Dolliver, 1977). This was particularly problematic for the indirect hit category (see Figure 1). Spokane (1979) and his contemporaries tabulated direct and indirect hits as two mutually exclusive categories or samples, which significantly increased the percentages reported. This contrasts with the method used in earlier studies, which calculated hit rates of all types (e.g., direct and indirect) using the entire sample. For example, Spokane reported direct and indirect good hits for males of 59.3% and 21.9%, respectively. However, using the entire sample of participants, as previous researchers had done, would have resulted in direct and indirect good hits of 45.3% and 5.1%, respectively, results that are more consistent with previous studies. It is important to note that Spokane's original approach also inflated the "clean miss" category percentages calculated, which were also significantly greater for the indirect hit category (69.9% versus 16.5%) than previous studies had reported. However, the "clean miss" category frequently receives little attention and is not discussed. After careful consideration of the percentages reported by investigators, I recalculated hit rates using the entire sample as done in previous studies (McArthur, 1954; Dolliver et al., 1972; Worthington & Dolliver, 1977). These percentages were recalculated for two reasons: (a) to increase comparability across all studies reported in Tables 1 and 2; and (b) to increase the meaningfulness of the hit rate percentages reported, as many of the original studies reported extremely high excellent indirect hit rates (e.g., 99%; see Figure 1).

Spokane (1979) investigated the predictive validity of the SCII for college-aged men and women using the McArthur method. This study represented the first attempt by a researcher to conduct validity testing with the Strong on a sample of female participants. Spokane classified participants by developing a "blind list" of all occupational preferences noted by subjects and then matching these with an appropriate scale from the SCII, independent of other information (i.e., gender, participants' entire

Figure 1

Example of Recalculated Results (RC): Hansen & Tan (1992) Concurrent Validity Condition (Males, N=47)



occupational profile). Substitution was required when both a male and female scale were not available with an identical name. Due to classification difficulties, 69 females and 50 males were omitted, as well as 18 females and 25 males identified as being undecided. This study was unique in that it also utilized a multivariate analysis to assess possible differences between the McArthur group classifications on levels of satisfaction, perceived congruence, differentiation, consistency, congruence, and whether or not they had attended counseling for any reason (Spokane, 1979).

Predictive validity percentages were calculated by comparing scores achieved on the 1974 administration of the SCII and occupational preferences noted by participants in 1978. As shown in Table 1, which shows my recalculations of the hit rates as described above, females showed fewer “direct good hits” than males (33.5% versus 45.3%, respectively). Nonetheless, the overall hit rates were similar to those achieved for male populations discussed previously. Results for the indirect good hit category displayed commensurate results across gender groups (4.6% for females versus 5.1% for males). These results differ from those reported by Gottfredson and Holland (1975), who found significantly higher and consistent hit rates for female than male participants over one- and three-year periods with the SDS. In their study of 989 female participants and 894 male participants, females and males had hit rates of 66.4% and 39.6% respectively, over a one-year period, whereas females and males had hit rates of 58% and 42% respectively, over a three-year period. Caution needs to be exercised in comparing these results, as Gottfredson and Holland (1975) only required the first letter in a participant’s three-point code to match their vocational aspiration.

In Spokane's multivariate analysis, only one of the univariate F values was significant [$F(1,446)=12.42$, ($p<.005$)]. For women, hit rates were higher for those who had attended counseling. This finding highlights the possibility that women who attend counseling sessions are more inclined, as compared to women who did not attend counseling to make decisions based upon their interests (Spokane, 1979).

As the previously mentioned information illustrates, numerous studies were performed on the Strong interest test over a period of 50 years, helping to establish its predictive abilities. The period between 1985 and 1994 saw a significant decrease in research on the Strong interest test. However, 1994 marked renewed interest in the SII, as professionals and researchers received the latest version of this instrument.

Hansen and Dik (2004) investigated the 12-year predictive validity of the Occupational Scales on the SII. Their efforts represent the most contemporary work available that has utilized the McArthur method. Predictive validity percentages over eight- and twelve-year time periods were calculated for men and women separately and together. However, they only reported the results for the twelve-year time period. Participants were further classified as being satisfied or not satisfied with their occupations. Here and in Table 1, I summarize the 12-year results.

The hit rates for men and women were similar to those in previous studies. The percentage of excellent direct hits for females was 32.5%, and 33.3% for males. The percentages of excellent indirect hits were somewhat higher for females (14.2%) than for males (8.6%). Participants whose occupation did not correspond to an occupation on the SII profile were removed from this study. "Two experts" were responsible for making indirect hit classifications when a direct match was not possible. The authors remarked that several of the participants' OS scores were used to create an indirect match. They provided the following example: "The individual who listed paralegal assistant was matched to the Lawyer, Librarian and Secretary scales" (Hansen & Dik, 2004, p. 370). Previous research has noted how this approach to classifying indirect hits could result in inflated hit rates (Zytowski, 1976).

Interestingly, none of the studies previously mentioned have asked the fundamental question of what constitutes an acceptable hit rate. Zytowski (1976) contended that concurrent hit rates should exceed predictive rates. Extrapolating from characteristics of the normal distribution, he speculated that concurrent hit rates should be around 70%. Zytowski stated "that the top limit for predictive validity lies at about one-third scoring highest on their own scale, and between one-half and two-thirds scoring at a level that would allow their own scale to be suggested to them as worth considering" (Zytowski, 1976, p. 222).

Zytowski (1976) investigated the 12- and 19-year predictive validities of the KOIS, while also attaining a chronological account of all jobs held by participants, level of job satisfaction, and success in their occupations. Zytowski's classification method was similar to McArthur's method. A "hit" was a direct match between a participant's occupation and a scale (i.e., either Occupational or College Major) on the KOIS. A "near miss" was analogous to moderate and poor hits in previous studies. Nearly half of all participants (N=439) were classified in the near miss category, which is substantially more than in previous studies. Three "experienced counselors" were responsible for making indirect hit classifications when a direct match was not possible (Zytowski, 1976, p. 225). Specific criteria for exclusion from the study included being unemployed, having an invalid profile, being a homemaker for more than 50% of the time, and having an inability to match participants' occupations with an appropriate scale on the KOIS. This resulted in 202 participants being excluded from the study. This study made a significant contribution to the area of research, by its application of a method that can be considered analogous to McArthur's on a different interest inventory, but also by the demographics of the sample used. One of the major shortcomings of the validity research conducted on the SII involves the rather homogenous samples used in investigations. Most participants in these studies have been Caucasian college graduates. Zytowski's (1976) sample was more representative of the general population, as he included a much wider range of participants, geographically (e.g., eastern seaboard) and demographically. His sample included the highly educated (e.g., Duke University students and physical therapists), but also included validity data from younger (e.g., eighth graders) and less economically advantaged individuals (e.g., participants from Forsythe County, North Carolina).

In the entire sample, Zytowski reported hit rates that were somewhat higher than in previous studies (51.3%). However, when specific populations were considered, a different picture emerged. Hit rates ranged from 100% for physical therapists (N=7) to 27.1% for individuals from the Forsythe County sample. Several patterns emerged as a function of occupational title and socioeconomic status (SES). Although specific percentages were not provided, Zytowski (1976) remarked that hit rates for engineering students were significantly higher than hit rates for other subpopulations. Zytowski contended that, due to the large number of engineering students represented, this "influenced the overall predictive findings" (p. 226). These results contrast those found for participants of lower SES (N=36). Similar to other findings, a pattern also emerged that supported greater predictive accuracy as a function of age during initial administration, with greater accuracy achieved as individuals mature. Predictive validity hit rates were also calculated by rank-ordering participants' top ten Occupational Scales. Results that matched an individual's occupation with the scale ranked as number one on the KOIS showed the highest percentages (11.5%). Overall, more than 53.5% of participants displayed congruence between their occupation and an OS on the KOIS ranked in the top ten. Zytowski also investigated how well the College Major scales predicted occupational membership over a span of three to eight years. This sample was comprised of participants (N=229) identified as being in grades eight through twelve. Overall, hit rates were comparable to those previously mentioned, shown at 55.4%; near hits were 25.4%; and misses were 19.1%. As previously mentioned, results fluctuated significantly by population studied (62.7% to 27.0%), which Zytowski (1976) attributed to SES differences (Zytowski, 1976).

Rottinghaus, Coon, Gaffey and Zytowski (2007) extended these findings by examining the predictive validity of the KOIS over a 30-year period with a different sample. Currently, this represents the only study to investigate the predictive abilities of an interest inventory over such an extensive time period. This study differed from those previously mentioned, as predictive validity was measured by employing Brown and Gore's (1994) C-index. The sample was comprised of 106 participants who were administered the KOIS in high school in the 1975–1976 school year and again in 2005. The first two authors converted participants' current occupations to Holland's six-point codes (i.e., RIASEC typology), utilizing the *Dictionary of Holland Occupational Codes* (DHOC). Holland's codes were then compared to a participant's 10 Activity Preference scale scores achieved during the 1975–1976 administration. Congruence was then measured between these two Holland code types using Brown and Gore's C-index, which quantifies the degree of match between the first three letters of two Holland codes (i.e., C=3(X)+2(X)+(X)). The level of congruence is calculated by supplanting the Xs with either a 3 (identical match), 2 (adjacent position on hexagon), 1 (alternate position on hexagon), or a 0 (opposite hexagon position). This calculation produces a range of scores from 1 to 18 and a theoretical mean of 9.0. Results for males (10.60) and females (10.22) were considered "predictive" as they were greater than the mean C-index (Rottinghaus et al., 2007).

In summary, research concerning the ability of interest inventories to accurately predict occupational choice is vast, spanning 70 years. During this time period, researchers have strived to create more explicit terminology, establish validity estimates independent of gender or SES, define an appropriate criterion, and refine methods to validate interest inventories over extended periods of time. Most importantly, these studies illustrate the inherent complexity involved in matching the results of interest inventories to participants' occupations. As Table 1 demonstrates, direct hits in the predictive validity studies for the top two categories (i.e., either good and poor or excellent and moderate) using the McArthur method ranged from 32% to 54.3%, whereas indirect hits ranged from 7% to 19.6%. Overall, Table 1 shows fairly consistent direct hit rate percentages across studies over time and gender. As one would suspect, there is also a trend of diminishing hit rates or ability of the test to predict future occupations within a study over time. This trend is clearly indicated by Worthington and Dolliver's (1977) study, which witnessed a 16% decline between the two time periods investigated (12-year and 18-year predictive validity estimates). I will now address studies that have investigated the ability of interest inventories to "predict" concurrent occupations.

Concurrent validity. Although predictive validity studies emerged first, many studies have tested both predictive and concurrent validity. Dolliver et al. (1972) was the first to conduct such an investigation. Concurrent validity percentages for the counseling-interpretation framework were mixed when compared to the predictive condition. The "*extremely descriptive of their present job*" category was smaller (at 34%) than in the predictive validity condition (43%). However, the "*some use*" and "*miss*" categories were larger in the concurrent condition (32% and 34%, respectfully) than in the predictive condition (29% and 28%, respectively). Concurrent validity results for the 1969 Strong administration yielded nearly identical results to that of the predictive condition (see Table 1). Only 65 participants were omitted based upon an inability to supply an accurate corresponding occupation on the SVIB. A chi-square test indicated that there was no significant impact on individuals who received interpretative feedback about their test results, in that feedback did not influence them to pursue their currently held occupation (Dolliver et al., 1972).

Worthington and Dolliver (1977) conducted a follow-up study to assess concurrent hit rates for the 1975 administration of the SCII. Although "exact agreement between raters was 83%," six participants were omitted due to an inability to accurately supply an appropriate occupational classification (Worthington & Dolliver, 1977, p. 211). Classifications for this study were based upon participants' reports, not the estimates imparted by the researchers. The authors stated that this was a more precise way of supplying an appropriate occupational classification as "the subject understands his job functions better than an experimenter who must make a judgment based only on knowledge of stated job preference, college major, or job title; but who usually has little knowledge of the actual job function of each subject" (Worthington & Dolliver, 1977, p. 211).

Worthington and Dolliver (1977) then compared the concurrent validity of the 1975 administration of the SCII (N=85) to that of the 1969 administration of the SVIB (N=59). A broader set of occupational classification rules were employed yielding a large increase in "indirect" classifications being made (Worthington & Dolliver, 1977).

Results regarding the reliability of the McArthur method produced some very interesting findings. Concurrent validity results were consistent with those found in previous studies; however, when investigators reviewed individual stability, a different picture emerged. Only 29% of participants' occupational classifications remained unchanged over the six-year period between studies. The greatest change in classifications was due to different rules being imparted, implicitly and explicitly. In a review of previous studies, the authors (Worthington & Dolliver, 1977) noted that, even when raters imparted explicit rules, agreement was only shown at an average of 76%. The area accounting for the second greatest amount of classification change was due to OS scores reported on the SVIB. Worthington and Dolliver (1977) reported no significant effect on validity due to participants changing jobs and/or participants' job titles changing during the six-year period.

Spokane (1979) built upon Worthington and Dolliver's study by comparing individuals' 1978 SCII scores and occupational preferences. In general, concurrent validity percentages showed a significant increase from previous studies. Results showed

61% good and poor direct hits for females. Hit rates for males were even higher (66.2%). However, after calculation methods were accounted for (i.e., sample size used for hit percentage tabulation) indirect good and poor hits for males (21.7%) and females (7.2%) were consistent with previous studies. Spokane (1979) stated that his direct hit results were only “slightly higher” than previous studies. However, previous research indicates the highest previous concurrent hit rates were 46% (Dolliver et al., 1977). Spokane (1979) did later note that the “classifications and validity coefficients in this study reflect idiosyncrasies of a single rater rather than real validity differences” (Spokane, 1979, p. 317).

A study by Donnay and Borgen (1996) was the first study to assess the validity, structure, and content of the newly revised 1994 SII. One of the major advancements put forth by this version of the SII was the sample upon which it was normed. Significant efforts were placed upon attaining a sample that was more representative of the general population of people who are very satisfied with their given occupation. This represents the trend toward producing an instrument that is valid across genders and ethnicities. Donnay and Borgen’s (1996) sample is referred to as the general reference sample, consisting of 9,467 females and 9,484 males. This study was similar to Borgen’s (1972) study in its focus on differentiating one occupation from another on the Occupational Scales, Basic Interest Scales, but also included the Personal Style Scales (PSSs). This advanced Borgen’s previous work through the provision of effect sizes and a multivariate analysis computed for the mean occupational differences.

Univariate analysis was performed in an effort to demonstrate that the 50 occupational groups averaged differently on the 35 Occupational Scales. All of the

Occupational Scales exhibited significant main effects for occupational group ($p<.00005$), showing the ability of the OS's to differentiate the 50 different occupations from one another. Donnay and Borgen (1996) stated that most of the scale differences displayed large effect sizes accounting for 15% or more of the variance. The Work Style scale displayed the greatest differentiation of all scales in its ability to separate the 50 occupations from one another (Wilks's Λ = .7109), followed by the Basic Interest Scale of science (Wilks's Λ= .7573), and the Investigative GOT scale (Wilks's Λ= .7753). Based in part on the robust sample size and in an effort to replicate results, participants were randomly assigned to two different groups for the multivariate analysis. The predictor variables of PSSs, BISs, and GOTs were used to predict occupational group membership. Wilks's lambdas were calculated from each predictor set. Results achieved for the 25 BISs were the most significant (Wilks's Λ= .0815), followed by the six GOTs (Wilks's Λ= .35) and the four PSSs (Wilks's Λ=.45). Overall, this pattern indicates that effect size increased as a function of the number of variables (i.e., more variables equaled a more significant effect). These results were then cross-validated with the other sample group to produce base and "direct hit" rates. Results supported those found in the first validation group. The PSSs produced "direct hit" rates of four times greater than chance. The GOTs yielded "direct hit" rates five times greater than chance, and the BISs produced the most significant results with "direct hit" rates ten times greater than chance (Donnay & Borgen 1996). Results such as these coincide with previous results (Borgen, 1972) and further indicate the ability of the SII to differentiate occupational group membership using the 35 scales comprised of the PSSs, GOTs, and BISs.

Historically, one of the most significant limitations in interest inventory research involves the ethnic homogeneity of the samples used. The studies previously cited demonstrated this limitation, as a majority of participants were Caucasian college students (Borgen, 1972; Dolliver et al., 1972; Donnay & Borgen, 1996; Hansen & Dik, 2005; Hansen & Neuman, 1999; Hansen & Swanson, 1983; Hansen & Tan, 1992; McArthur, 1954; Schletzer, 1966; Spokane, 1979; Strong, 1935, 1955; Worthington & Dolliver, 1977). Lattimore and Borgen (1999) were the first to address these limitations using the national norm sample of the 1994 SII. Although the majority of individuals (17,365) were identified as Caucasian Americans, the sample also included the largest concentration of other ethnicities examined in validity research thus far (378 African Americans, 363 Asian Americans, 349 Hispanic Americans, and 77 Native Americans). Concurrent validity was examined by comparing participants' primary GOT code types to the code types of their current occupations. For example, if a participant was a clinical psychologist, their code type would be IAS, which would then be matched with the first letter of their GOT results. A multivariate analysis was conducted to determine the ability of the GOTs to differentiate concurrent occupations. In the total sample, the direct hit rate was 41.8% and 48% of the variance in occupational group membership could be accounted for by the GOTs. When ethnicity was considered, variance percentages ranged from 43% (Asian American) to 71% (Native American). Direct hit rates were lowest for African Americans (40%) and highest for Native Americans (55.3%).

These rates are commensurate with other findings. Nonetheless, the authors (Lattimore & Borgen, 1999) believed that the limited number of Native American participants inflated their results. Another limitation of this study was a failure to provide specific information on how hit rates were calculated. The authors used only one classification of a "hit," whereas previous research has specified the quality of hits ranging from poor to excellent. The authors also failed to provide specific information on how they matched a participant's current occupation with an applicable Holland code. As previous studies have noted, this is a very complicated process that can significantly impact the results. In addition, no participants were excluded on the basis of being unable to supply the correct occupational classification, which has been shown to be common (Dolliver et al., 1972; Strong, 1935, 1955; Worthington & Dolliver, 1977). Although this study represented a major stride forward by examining the utility of the SII with ethnic minorities, the educational level of the sample compromised its generalizability. On average, participants' educational levels ranged from an associate degree (Native Americans) to master's level (Asian Americans). Despite these limitations, this study made a significant contribution by examining the results of non-majority populations.

In a recent concurrent validity study, Flores et al. (2006) addressed the issue of educational status and level of SES by surveying 487 (272 females and 215 males) Mexican American high school students, ranging in age from 15 to 18 years. The demographic characteristics of this sample represented a significant departure from other studies. Participants resided in close proximity to the Mexican border and represented a population characterized as being of lower SES, with median household income just over $20,000 and 48% of children living in poverty. Concurrent validity was assessed by matching participants' expressed career aspirations to the GOTs on the SII. Calculations were performed on these two data points by employing Brown and Gore's (1994) congruence index. Results indicated that the SII had the ability to predict concurrent career aspirations and displayed commensurate values to those found in other studies (Rottinghaus et al., 2007). These results were in slight contrast to those Rottinghaus et al. (2007) found, as females (M=10.79) displayed greater congruence scores than males (M=10.22). Although these results are comparable to previous studies, there were a couple of limitations. These results need to be viewed with an understanding as to the role maturation plays with respect to interests, as previously mentioned. The authors (Flores et al., 2006) also failed to measure the level of acculturation present in this sample. It would be interesting to see how these two variables affect these results.

The interest inventories discussed here were initially developed and normed on American populations and few researchers have assessed their validity with non-American populations. Leung and Hou (2001) conducted an investigation to address this limitation. Their study assessed the concurrent validity of the SDS with 777 (456 female and 321) Chinese high school students in Hong Kong. Similar to the investigation Rottinghaus et al. (2007) conducted, hit rates were analyzed by comparing the first letter of their Holland three-point code with their tentative occupational and academic choice. For all participants, hit rate percentages were calculated by assessing the level of congruence between these two data points. Exact hits for females in the occupational choice group (40.8%) were significantly higher than for males (28.6%), whereas adjacent hits were only slightly higher for females (28.6%) than males (27.6%). These percentages were significantly lower than those in the Caucasian sample studied by Holland et al. (1994). Therefore, Leung and Hou's (2001) results could represent the cultural limitations of the SDS when applied to a sample of Chinese adolescents residing in Hong Kong.

In summary, this area of research is significantly advanced by these studies, as they included participant reports when making classification decisions, assessed the stability of McArthur classifications, employed significantly larger samples, and investigated all of the scales on the SII. Most importantly, these studies addressed limitations imposed by previous studies that failed to include more ethnically and educationally diverse populations. When viewed as a whole, all of these factors greatly advance the generalizability and limits of interest inventories. As Table 1 demonstrates, direct hits for the top two categories (i.e., either good and poor or excellent and moderate) using the McArthur method ranged from 40% to 66.2%, whereas indirect hits ranged from 7.2% to 26%. Zytowski's hypothesis that concurrent hit rates should be greater than predictive hit rates was moderately supported as two out of the three studies that investigated both of these constructs demonstrated higher concurrent than predictive hit rates. However, this finding needs to be viewed from the perspective that one of these three studies was Spokane's (1979) study that produced significantly higher direct hit rates than any other study listed in Table 1.

Interest Tests and College Major Choice

Predictive validity. As mentioned previously, the Occupational Scales on the SII represent the most precise measurement with respect to occupational choice, but have also been utilized to predict college major selection. Borgen (1972) was one of the first to assess the predictive validity of the OS and the BISs on the SVIB using undergraduate major as the criterion variable. Borgen selected participants with superior scores on the Scholastic Aptitude Test (SAT) and winners of the National Merit Scholarship. The study was comprised of two groups: undergraduate college students (N=1,031) and individuals in a career field (N=780). Those identified as being in the undergraduate group were placed in 16 different major categories. This study included a follow-up with participants three years after they completed the SVIB. T-tests were conducted to establish how well a given OS and BIS were able to separate college majors from one another. Thus, less overlap denoted a scale that is better able to differentiate the criterion subgroup (e.g., psychology major) from all other majors present in the study (e.g., non-psychology majors). Of the 16 different majors, the OSs ranged in overlap from 53% (music teacher) to 90% (psychologist). BISs ranged in overlap from 54% (nature) to 89% (social services). Overall, when predicting college majors, the OSs showed a slight predictive advantage (lambda =.229) over the BISs, but the BISs displayed a slight advantage when predicting career choice in the individuals already in the career field.

Hansen and Swanson (1983) conducted a study to reassess the predictive validity of the SCII in predicting college choices. This study advanced research in this area in many ways. It had a significantly larger sample size for males and females, and it used a newly revised SCII that showed greater equality across genders on the Occupational Scales. This was the first study to employ Pearson product-moment correlation coefficients in an effort to assess profile stability between two administrations of the SCII (during the freshman and senior years). This study was also the first to assess expressed satisfaction with an individual’s declared major when calculating predictive validity percentages. Most importantly, this was the first study to use the McArthur method to predict college majors (Hansen & Swanson, 1983).

Hansen and Swanson (1983) built upon the classifications used by Worthington and Dolliver (1977). They used individuals' standard scores to classify excellent hits (greater than 45), moderate hits (40–45), and poor hits (below 39). When results indicated a "flat profile" (i.e., no Occupational Scales above 45), they selected an individual's three highest scores.

In the female sample, predictive validity percentages produced results similar to Spokane's (1979) results for occupational choice, with 36.7% direct and 7.7% indirect excellent hits. However, in the male sample, there were 25.6% "direct excellent hits," significantly less than Spokane's (1979) previous results (Hansen & Swanson, 1983). Hansen and Swanson also explored the possible moderating effect that satisfaction with one's major had on the SII predictive hit rates. Overall, results showed that the SII OS scales displayed greater predictive power for the group identified as being satisfied than those who were unsatisfied (see Table 2). Combined excellent and moderate direct hit rates for the satisfied female and male groups were shown at 60.4% and 49.3%, respectively. Indirect hit rates for this group were 9.8% and 24.4%, respectively. This compares to the unsatisfied group, which displayed lower direct excellent and moderate hit rates of 43.2% and 35%, respectively. Indirect hit rates were 9.7% and 16.3% (Hanson & Swanson, 1983).

A second experiment was conducted in this study to assess individual interest stability from the validity of the instrument. This experiment blended the McArthur method with that of the profile stability assessment in experiment one, which identified two different categories: (a) stable and (b) unstable. Participants were subdivided by their hit classification and their individual profile test-retest correlations by first and fourth

Table 2

Recalculated hit rate results for concurrent and predictive validity studies concerning college major choice using the Strong Interest Inventory

Study	**Validity**	**Direct**		**Indirect**		**Total**	
		N	**%**	**N**	**%**	**N**	**%**
Hansen & Swanson (1983)							
Predictive Validly SCII	Excellent Hits	90	36.7	19	7.7	109	44.4
Females (N=245)	Moderate Hits	3	12.2	5	2.0	35	14.4
	Poor Hits	90	36.7	11	4.4	101	41.1
	Total	210	85.6	35	14.1		
Predictive Validity SCII	Excellent Hits	47	25.6	23	12.5	70	38.1
Males (N=183)	Moderate Hits	24	13.1	11	6.0	35	19.1
	Poor Hits	64	34.9	14	7.6	78	42.5
	Total	135	73.6	48	26.1		
Predictive Validity SCII	Excellent Hits	35	43.2	8	9.8	43	53.0
Satisfied with College Major	Moderate Hits	14	17.2	0.0		14	17.2
Females (N=81)	Poor Hits	22	27.1	2	2.4	24	29.5
	Total	71	87.5	10	12.2		
Predictive Validity	Excellent Hits	16	32.6	8	16.3	24	48.9
Satisfied with Academic Major	Moderate Hits	8	16.7	4	8.1	12	24.8
Males (N=49)	Poor Hits	11	23.1	2	4.0	13	27.1
	Total	35	72.4	14	28.4		
Predictive Validity	Excellent Hits	55	33.5	11	6.7	66	40.2
Unsatisfied with College Major	Moderate Hits	16	9.7	5	3.0	21	12.7
Females (N=164)	Poor Hits	68	41.4	9	5.4	77	46.8
	Total	139	84.6	25	15.1		

Study	Validity	Direct		Indirect		Total	
		N	%	N	%	N	%
Hansen & Swanson (1983)							
Predictive Validity	Excellent Hits	31	23.1	15	11.1	46	34.2
Unsatisfied with College Major	Moderate Hits	16	11.9	7	5.2	23	17.1
Males (N=134)	Poor Hits	53	39.5	12	8.9	65	48.4
	Total	100	74.5	34	5.2		
Concurrent Validity	Excellent Hits	91	40.6	22	9.8	113	50.4
SCII Time 1 (Freshman year)	Moderate Hits	34	15.1	1	.5	35	15.5
Females (N= 224)	Poor Hits	71	31.6	5	2.2	76	33.8
	Total	196	87.3	28	12.5		
Concurrent Validity	Excellent Hits	47	30.9	29	19.0	76	49.9
SCII Time 1 (Freshman year)	Moderate Hits	25	16.4	2	1.3	27	17.7
Males (N=152)	Poor Hits	47	30.9	2	1.3	49	32.2
	Total	119	77.3	33	21.6		
Concurrent Validity	Excellent Hits	120	48.9	25	10.2	145	59.1
SCII Time 2 (Senior year)	Moderate Hits	34	13.8	5	2.0	39	15.8
Females (N=245)	Poor Hits	56	22.8	5	2.0	61	24.8
	Total	210	85.5	35	14.2		
Concurrent Validity	Excellent Hits	80	43.7	37	20.2	117	63.9
SCII Time 2 (Senior year)	Moderate Hits	22	12.0	7	3.8	29	15.8
Males (N= 183)	Poor Hits	33	18.0	4	2.1	37	20.1
	Total	135	73.7	48	26.1		
Hansen & Tan (1992)							
Concurrent Validity SII	Excellent Hits	35	47.9	17	23.3	52	71.2
Females (N= 73)	Moderate Hits	5	6.8	1	1.4	6	8.2
	Poor Hits	14	19.1	1	1.4	15	20.5
	Total	54	73.8	19	26.1		

Study	Validity	Direct N	%	Indirect N	%	Total N	%
Hansen & Tan (1992)							
Concurrent Validity SII	Excellent Hits	16	34.0	20	42.5	36	76.5
Males (N= 47)	Moderate Hits	1	2.1	2	4.3	3	6.4
	Poor Hits	8	17.0	0	0.0	8	17.0
	Total	25	53.1	22	46.8		
Hansen & Neuman (1999)							
Concurrent Validity CISS, OS	Excellent Hits	14	22.6	19	30.6	33	53.2
Females (N= 62)	Moderate Hits	4	6.4	6	9.7	10	16.1
	Poor Hits	10	16.1	9	14.5	19	30.6
	Total	28	45.1	34	54.8		
Concurrent Validity CISS, OS	Excellent Hits	16	24.3	16	24.3	32	48.6
Males (N= 66)	Moderate Hits	4	6.1	2	2.7	6	8.8
	Poor Hits	9	4.0	4	6.3	13	20.3
	Total	29	44.4	22	33.3		
Concurrent Validity CISS, OSS	Excellent Hits	14	21.8	19	31.3	33	53.1
Females (N= 62)	Moderate Hits	2	3.3	3	8.6	5	11.9
	Poor Hits	12	19.9	12	18.8	24	38.7
	Total	28	45.0	34	58.7		
Concurrent Validity CISS, OSS	Excellent Hits	15	22.7	20	30.3	35	53.0
Males (N = 66)	Moderate Hits	2	3.0	3	4.5	5	7.5
	Poor Hits	12	18.0	14	21.2	26	39.4
	Total	29	43.7	37	56.0		
Concurrent Validity SII, OS	Excellent Hits	23	37.1	12	19.4	35	56.5
Females (N= 62)	Moderate Hits	3	4.8	2	3.2	5	8.0
	Poor Hits	20	32.3	2	3.2	22	35.5
	Total	46	68.8	16	25.8		

Study	**Validity**	**Direct**		**Indirect**		**Total**	
		N	**%**	**N**	**%**	**N**	**%**
Hansen & Neuman (1999)							
Concurrent Validity SII, OS	Excellent Hits	20	30.3	15	22.7	3	53.0
Males (N= 66)	Moderate Hits	4	10.6	6	9.1	10	19.7
	Poor Hits	16	24.2	5	7.6	21	31.8
	Total	40	65.1	26	39.4		
Hansen & Lee (2007)							
Concurrent Validity, SII[a]	Excellent Hits	40.4					
Asian Females	Moderate Hits	16.9					
(N= 89)	Poor Hits	42.7					
Asian Males	Excellent Hits	45.8					
(N= 59)	Moderate Hits	8.5					
	Poor Hits	45.8					
Caucasian Females	Excellent Hits	44.3					
(N= 97)	Moderate Hits	13.4					
	Poor Hits	42.3					
Caucasian Males	Excellent Hits	60.8					
(N= 74)	Moderate Hits	20.3					
	Poor Hits	18.9					

Note. Due to rounding, the marginal total percentages do not all sum to precisely 100%.

[a]Only direct hit classifications were provided by the authors.

quartiles. The McArthur method showed greater stability than previous studies. Correlations ranged from a high of r=.84 for males in the excellent hit category, to a low of r=.64 for males in the poor hit category. This indicates a slight relationship between stability and hit classification, in that individuals identified as having an unstable profile were more likely to be in the “poor hit” category than in the “excellent” hit category. Females identified as having stable interests were twice as likely (shown at 60%) to be placed in the “excellent direct hit,” compared to females having unstable interests (shown at 29%). These results were not limited to the female sample, as males identified as having stable interests were 53% more likely to be placed in the “excellent hit” category, compared to those displaying unstable interests (shown at 9%) (Hansen & Swanson, 1983). These results are comparable to those noted in previous studies (Spokane, 1979).

Although this study advanced this area of research in many ways, there were two notable shortcomings. Most notable was the lack of information on how “indirect” classifications were made. The authors stated that the “SCII was particularly successful at predicting major fields when free of the restriction of one-to-one matching with the available Occupational Scales” (Hansen & Swanson, 1983, p. 198). Another notable difference between this study and those previously described is the fact that no participants were omitted due to classification difficulties. The liberal approach taken by the authors when assigning hit classifications is illustrated in the previous quote.

In summary, this section provided additional evidence for the validity of interest inventories by showing their ability to predict college majors. Studies advanced the analysis of profile stability by employing Pearson-product moment correlations, showed the ability of the OSs and BISs to differentiate one college major from another, and provided explicit terminology specific to addressing a "flat profile." This section also highlighted persistent limitations in researchers' failure to include specific terminology on how they made indirect classifications. Direct hits concerning the top two categories (i.e., either good and poor or excellent and moderate) using the McArthur method were comparable to previous studies and ranged from 35% to 60.4%. Indirect hits were also comparable and ranged from 9.7% to 24.4%.

Concurrent validity. Many researchers have tested the concurrent validity of interest tests with college major choice in the past 20 years. Hansen and Swanson (1983) were the first to do so. They calculated concurrent validity percentages at two time points. The authors omitted 106 participants who were not currently enrolled in courses. For time one, the authors selected individuals from a freshman orientation class. For the freshman, female participants produced slightly higher direct excellent and moderate hits (55.7%) than males (47.3%). However, for the indirect hits, males (20.3%) displayed higher results than females (10.25%). Results concerning time two (i.e., during their senior year) displayed an increase in scores across all categories. For females, percentages of direct excellent and moderate hits were slightly higher (62.7%) than for males (55.7%). Males also displayed higher indirect hit rates for excellent and moderate categories (24%) than females (12.2%). This increase in "excellent" and "moderate hit" rates might be linked to the greater stability of interests as a function of maturation. Also, the college majors of some freshman may not be well-considered or their final choice.

In 1985, major revisions to the Occupational Scales were performed. This resulted in more professional level occupations being represented, as well as greater inclusion of nonprofessional occupations (e.g., technical occupations). Due to extensive modifications in the construction and standardization of the OSs, Hansen and Tan (1992) performed a follow-up investigation similar to the study previously noted. Thus, they utilized the McArthur method, with college major as the criterion, and assessed for degree of satisfaction with their major.

Participants in this study were identified as 120 “college students enrolled in an introductory psychology class at a large Midwestern university” (Hansen & Tan, 1992, p. 54). Participants’ own-sex scores were utilized as the predictor variables and as a means to classify them into the appropriate hit categories based upon their identified majors. Participants displayed a high level of congruence (95%) between their declared major and intended occupation upon completion of their degree. Contrary to the results of the previous study (Hansen & Swanson, 1983), only four individuals expressed dissatisfaction with their majors. Participants (N=22) identified as having more than one major were classified using the major that provided the highest hit classification based upon their testing results. In the total sample, 34.2% were placed in the “indirect hit” category, compared to 65.8% in the “direct hit” category shown. Being placed in the “indirect hit” category resulted in being matched with several OSs that were then assigned a corresponding major based upon the highest OS score. Hansen and Tan (1992) provide the following example: “If a student majoring in music therapy scored 56, 41, and 29, respectively on the ‘indirect’ match scales of Occupational Therapist, Special Education Teacher, and Musician, she or he was assigned to the ‘excellent’ category based upon the score of 56 on Occupational Therapist” (p. 55).

Results showed no significant difference between participants who had stated that they declared a major (N=70) and those who had only stated an intention to declare a given major (N=48) [χ^2 (2, N = 118) = .413, p = .813]. As Table 2 shows, concurrent hit rates in the direct excellent and moderate categories were higher for females (54.7%) than for males (36.1%). However, this difference by gender was not shown to be significant [χ^2(1,N=120) = .22, p = .639]. The indirect excellent and moderate hit categories produced some very interesting findings in that they accounted for 46.8% of males.

This study further advanced the body of literature regarding the SCII by replicating results produced previously. It provided greater detail with respect to how participants in the "indirect" hit category were classified. Based upon previous results, it is still surprising that no participants were omitted due to classification difficulties. This is also the first study to mention the limited generalizability of results based upon a rather homogenous sample, being identified as 90% Caucasian. The sample size in the present study was considerably smaller than in Hansen and Swanson's 1983 study (N=120 versus 428). Another possible limitation of this study relates to the changes made to the OSs, which were more inclusive of nonprofessional occupations. However, it is likely that the impact of these OS changes was not assessed because of the sample being oriented toward professional occupations.

Hansen and Neuman (1999) compared the power of the SII to that of the CISS in predicting participants' identified college majors. A total of 50 academic majors were represented by 128 participants (62 females and 66 males) who were surveyed in an introductory psychology course. Hit rates were calculated for these two interest inventories by comparing participants' Occupational Scales (OS) on the CISS to the Occupational Scales on the SII. Hit rates were also calculated for the Occupational Skill Scales (OSS) on the CISS. Only participants identified as being satisfied or very satisfied with their college major were included in this study. The OS scores for the CISS produced excellent and moderate hits for 29% of females and 30.4% of males. Results for the OSS of the CISS were comparable, shown at 25.1% for females and 25.7% for males. Hit rates for the SII OS scales were higher, 41.9% for females and 40.9% for males. This study further promoted validity testing by including more than one instrument and both interests (OS) and skill confidence (OSS) scales.

However, Hansen and Neuman's study (1999) had some limitations. One was the small sample examined. There were as few as 16 participants for the female indirect category of the SII. This modest sample size leads to speculation on how many participants were represented in their prospective majors, given that 50 majors were represented in this study. It also appears that the authors' liberal approach to matching OSs to appropriate college majors was extended by including all participants, but also by selecting the academic major (for those identified as having more than one major) that corresponded to the highest OS score.

Hansen and Lee (2007) recently published a study that provided a different comparison. This comparison was the first of its kind, as it compared concurrent hit rates utilizing a sample that was 54% Caucasian and 46% Asian American. This study also addressed the limitations present in previous investigations (Flores et al., 2006; Zytowski, 1976) by providing a measure of acculturation and by examining hit rates within the specific majors of psychology, teaching, business, and technical or engineering areas. Overall, 60 majors were represented in this investigation, which served as the criterion. Hit rates were calculated using the McArthur method. Interestingly, the authors did not exclude any participants due to difficulty assigning an Occupational Scale that matched their academic major, so this is the first time that all participants received a direct match classification. Results for excellent and moderate direct hits for Asian American women, Asian American men, Caucasian women and men were slightly higher than most of the other investigations discussed, shown respectively at 57.3%, 54.3%, 57.7%, and 81%. The authors noted that the disproportionately large number (N=34) of male Caucasians whom were identified as being in the highly predictable (91%) business major elevated these hit rates. Another notable result was that concurrent prediction of the four specific majors ranged from 0% (Caucasian females in technical/engineering majors) to 100% (Asian females in business and Caucasian males in teaching). These results are in partial support of McArthur's original claims regarding the predictability of certain disciplines. Acculturation did not moderate the predictive power of the SII.

The last study addressed was conducted by Gasser, Larson, and Borgen (2007), who attempted to ascertain the concurrent validity of the newly revised 2005 SII. This article is important for three reasons: (a) it was the first attempt to assess the concurrent validity of the 2005 SII; (b) it utilized gender and major field of study as the criteria; and (c) it attempted to clarify the concurrent predictive power of single scales and various combinations of the GOTs, BISs, and the five PSSs content scales. The authors put forth the following three hypotheses: (a) addition of the BISs to the other content scales will significantly enhance the concurrent predictive ability of the SII; (b) the BISs alone will have more predictive power than the GOTs or PSSs; and (c) validity generalization will be achieved by examining the fit between males and females.

Participants (N=1,872) for this study were selected from the national college sample obtained by the test publisher, CPP Incorporated (Gasser et al., 2007). These participants were solicited through the same means used to attain the General Reference Sample (GRS), used to norm the most recent SII. However, no information was provided by the authors to clarify if the "national college sample" is encompassed by the GRS sample or if it is a completely different sample. There is also no mention of this sample in the 2005 SII manual (Donnay et al., 2004). Therefore, it appears that the authors took the liberty of labeling their sample as the "national college sample" by conducting an analysis on the dispersion of regional area codes noted by participants. This sample was made up of individuals (female, N=1,403; male, N= 469) who were enrolled full-time, ranged in age from 17 to 57, and were 73% Caucasian, 11% African American, 8% Hispanic, 5% Asian, and 3% other or multiple ethnicities.

Due to the clear disparity in the number of males relative to females in this sample, the males were utilized as a means of validity generalization, whereas the female sample was used in the discriminant analysis function. That is, the models that were generated for the female sample using multivariate techniques were then "fit" to the data for the male sample (Gasser et al., 2007). There were 75 different majors identified across genders, with fewer than 16 students not included in the analysis. This procedure reduced the number of majors to 31, yielding a "chance" hit rate of 3.2%. The "jackknife" procedure was also utilized in an effort "to correct for inflated hit rates due to overweighting sample-specific error"; this "procedure generates a new hit rate by re-running the analysis multiple times by removing a case and then replacing it" (Gasser et al., 2007, p. 30).

The authors' first two hypotheses were supported because adding the BISs significantly increased the predictive power of the SII. The hit rates for females were

12.9% for the PSSs, 15.3% for the GOTs, and 33.7% for the BISs. Combining the PSSs and GOTs resulted in a hit rate of 20.3%, whereas the combination of the PSSs, GOTs, and BISs resulted in a hit rate of 38.3%. When the jackknife method was employed, hit rates equaled 10.2%, 12.1%, 21.1%, 16.1%, and 22.3%, respectively.

The authors' third hypothesis was also supported because the results that were found for the female sample generalized to that of the male sample. Specifically, the BISs displayed the greatest predictive validity, predicting an individual's college major at a rate of six times better than by chance.

This study displayed two notable shortcomings. The first shortcoming was the lack of information provided regarding what constituted a "hit" or inclusion into a specific field of study. The other significant shortcoming related to the narrow selection of majors represented as compared to previous studies (Hansen & Swanson, 1983). Most of the majors in the present study were in Social, Artistic, and Investigative disciplines.

In summary, the research reported in this section significantly addresses previous limitations in this area of research in many aspects. It does this by comparing the hit rates of two interest inventories to one another, including a larger sample size, increasing the number of college majors represented, investigating combinations of SII scales, and by assessing hit rates for a minority population, while also including a measure of acculturation. It also introduced a new method of investigating hit rates. However, it is unclear how these were defined or compared to previous studies. Table 2 shows direct hits using the McArthur method for the top two categories (i.e., excellent and moderate) ranging from 25.1% to 57.7%, whereas indirect hits ranged from 10.2% to 46.8%.

Congruence-Satisfaction and Congruence-Achievement Hypotheses

The ability of person-occupation congruence to predict satisfaction or achievement has also been examined as another aspect of validity testing. Strong (1955) struggled with the idea of congruence when attempting to find the most suitable criterion for establishing the validity of the SVIB. Schletzer (1966) investigated the power of the SVIB to predict job satisfaction among a group of recently graduated professionals. Participants were administered the SVIB during their senior year of high school, and job satisfaction surveys were administered three years after graduation. Schletzer found no relationship between expressed interests and job satisfaction. This is reinforced by a study by Dolliver et al. (1972), in which no relationship was found for current job satisfaction and the corresponding score for this occupation on the SVIB. However, in a follow-up study, these investigators found support for E.K. Strong's original hypothesis that job satisfaction will correlate with Occupational Scale scores (Worthington & Dolliver, 1977). Spokane (1979) also found that people in different McArthur group classifications differed in satisfaction, perceived congruence, differentiation, consistency, and congruence. Findings such as these suggest that individuals identified as being in the "direct good hit" category will be more satisfied, differentiated, consistent, and congruent than their peers, regardless of gender. Indeed, a post hoc analysis revealed a moderate linear relationship between satisfaction and being identified as being in the "direct good hit" category (Spokane, 1979).

Spokane, Meir, and Catalano (2000) performed a meta-analysis on the congruence-satisfaction hypothesis and its predictive power based on the level of fit present between a person and environment. The results were disappointing, as correlations rarely exceeded .25, making it a tenuous relationship at best. A previous investigation by Assouline and Meir (1987), which explored both published and unpublished doctoral dissertations, produced similar findings (i.e., mean r of .21). In another meta-analysis, Tranberg, Slane, and Ekeberg (1993) found comparable results between person-environment congruence and job satisfaction (i.e., mean r of .20). However, person-environment congruence and academic satisfaction correlated less, with a mean of .095. Tsabari, Tziner, and Meir's (2005) meta-analysis produced even less encouraging results, with an overall mean correlation of .16.

The ability of person-occupation congruence to predict achievement has also been examined in a few studies. Holland (1985) hypothesized that high educational aspirations and high educational achievement go hand in hand. Furthermore, Holland (1985) stated that when students are "in congruent environments they will demonstrate higher achievement scores than students in incongruent environments" (p. 106). In support of his hypothesis, he cited a study conducted by Werner (1974), who investigated the vocational aspirations of 527 high school students. However, as other researchers (Schwartz, Andiappan, & Nelson, 1986) have pointed out, Werner never made reference to the congruence-achievement hypothesis. Warner (1974) instead focused on the clarity of role decisions and its connection to satisfaction and achievement. In an attempt to further clarify the congruence-achievement hypothesis, Schwartz et al. (1986) investigated the correlation between high-point codes and income among 555 female and 498 male accountants. Results showed an inverse relationship with respect to the achievement-congruence hypothesis. Specifically, male and female accountants who had Conventional high-point codes were shown to have lower incomes.

Bruch and Kreishok (1981) investigated the congruence-achievement hypothesis with a group of freshman engineering students. Contrary to the previously mentioned studies, their investigation demonstrated support for Holland's hypothesis. Participants who had Investigative as their highest code type were more successful in school than those that did not. However, as Schwartz pointed out, this study might be limited by the fact that Investigative types are more academically oriented (Holland, 1985).

A recent study conducted by Tracy and Robbins (2006) investigated the relationship between interest-major congruence and college success. Specifically, the level of congruence between a participant's interests and major were compared to two different outcomes (e.g., GPA and college persistence) at three different time periods (after year 1, after year 2, and after graduation). Their study included a robust sample size of 80,754 enrolled at 87 colleges. Holland RIASEC code types were assessed using the unisex edition of the ACT interest inventory. Results were clear with respect to interest scores and GPA, as those that had higher interest scores also had higher GPAs shown by multiple correlations (i.e., R^2) ranging from .107 to .154. By contrast, an inverse relationship was discovered between interest levels and persistence. Those who had lower interest scores were more likely to persist and graduate than those with a higher interest score with multiple correlations (R^2) ranging from .010 to .067. Tracy and Robbins (2006) hypothesized that this occurred because those with lower interest scores had more flexible interests, which in turn allowed for greater perseverance. The strength of these effects was very modest, however.

In summary, the studies found in this section attempted to test the hypotheses relating person-environment congruence to satisfaction and achievement. These hypotheses were investigated in academic and occupational environments. However, based upon the results of these studies, no definitive or strong relationship appears to exist between congruence and either satisfaction or achievement. What is more clearly established by these investigations is the level of complexity in measuring occupational or academic satisfaction and an inability of expressed interests (i.e., RIASEC type codes) to predict them.

Conclusion

This literature review describes the depth and breadth of research conducted in the area of validity testing on interest inventories. Specific information was imparted on the historical roots of validity studies, the wide use of the McArthur method, eventual inclusion of females, lower SES populations, ethnic minorities, and non-American populations. As shown in Table 1, the predictive validity percentages concerning occupational choice for direct, excellent, and moderate hits ranged from 32% to 54.3%. Indirect hit rates for these categories ranged from 7% to 19.6%. Concurrent validity percentages concerning occupational choice for direct, excellent, and moderate hits have ranged from 40% to 66.2%. Indirect hits have ranged from 7.2% to 26%. Table 2 displays the predictive validity percentages for college major selection with direct, excellent, and moderate hits ranging from 35% to 60.4%. Indirect hit rates for these categories ranged from 9.7% to 24.4%. Concurrent validity percentages for direct, excellent, and moderate hits have ranged from 25.1% to 57.7%. Indirect hits have ranged from 10.25% to 46.8%. Overall, hit rates have increased slightly over time, but have been fairly consistent across genders. Overall, these hit rate percentages are more accurate for “predicting” concurrent occupations and academic majors than predicting future occupations or academic majors.

These results also show moderate support for Holland’s (1985) hypothesis that individuals with certain interests or personalities will seek out the corresponding and supporting career and educational environments. Although Holland argued that the level of congruency is critical in predicting satisfaction and achievement within an individual’s career, these predictors have been modestly supported at best.

All of these results have significant implications for career counselors working with clients seeking academic or occupational assistance. If students score high on the engineering occupation, it is likely that they might consider this career as an option or may already be enrolled in that major field of study. However, as the previous information illustrates, a high score on the scale does not necessarily guarantee one’s happiness or ability to perform well. Therefore, caution needs to be exercised when providing interpretive feedback regarding interest inventory results. This may be especially true for clients who are experiencing pressure to select a major, both internally (e.g., anxiety) and externally (e.g., parents).

Several aspects of validity testing still warrant exploration. Hit rates using the McArthur method have not been examined with the most recent version of the SII. Most studies have only included participants at large midwestern universities. It remains unclear how well results from this population will generalize to other geographic regions or subpopulations. Lastly, as pointed out by Hansen and Lee (2007), more research is needed to examine the ability of specific OSs to predict concurrent college majors. Given the small number of studies and conflicting results, further research is warranted on the congruence-achievement hypothesis or performance-based outcomes.

Overview of the Present Study

This study investigated the concurrent validity of the GOT, BIS, OS, and PSS scores of the SII in predicting declared academic major as a criterion variable. For the OSs, I utilized the McArthur method to classify hits with concurrent academic majors of undergraduate students at WSU. For the GOT, BIS, and PSS scales I used multiple discriminant analyses to differentiate academic major groups. I also tested the congruence-achievement hypothesis by relating GOT congruence between test scores and declared major to cumulative GPA.

The specific hypotheses were as follows:

Hypothesis 1: Using the McArthur method, the Occupational Scales (OSs) of the Strong Interest Inventory (SII) will predict a participant's exact academic major (Direct Excellent Hit) for at least 35% of the sample.

Hypothesis 2: Using multiple discriminant analysis, the Basic Interest Scales (BISs) of the SII will show the highest level of accuracy in predicting participant academic major followed by the General Occupational Themes (GOTs) and Personal Style Scales (PSSs).

Hypothesis 3: Greater GOT congruence between individuals' interest scores and their academic majors will be associated with greater cumulative GPAs.

CHAPTER THREE

Methodology

Sample

The total sample consisted of 900 individuals who were referred for testing by Career Services at Washington State University (WSU). However, due to missing and incomplete information (e.g., gender, college major information not provided) the data set was reduced to 501 participants (304 females, 197 males). Participants were WSU students ranging in age from 20.08 to 48.67 who completed the SII during the period 2006-2009. The average age for participants in the total sample was 23.88 (SD = 3.72). The majority of participants identified as being Caucasian (70%) followed by Hispanic (13%), Asian (7%), African American (3%), multi-racial (1%), and American Indian/Alaska Native (<1%); 7% failed to indicate their ethnicity. All participants were drawn from the SII database made available by CPP Incorporated.

Instrument

The Strong Interest Inventory (SII) consists of 291 items that assess an individual's career interests and personal styles. Within the SII are four different sets of scales: six General Occupational Themes (GOTs), 30 Basic Interest Scales (BISs), 244 Occupational Scales (OSs), and five Personal Style Scales (PSSs). These scales have standard scores with means of 50 and standard deviations of 10. For the GOT, BIS and PSS scales, these T-scores are based upon a combined-gender general reference group. For the OSs, the T-scores are based on gender-specific normative samples in specific occupations. The broadest set of scales, the GOTs, represent Holland's six-personality types (Realistic, Investigative, Artistic, Social, Enterprising, and Conventional) and measure an individual's vocational interests and lifestyle preferences. The 30 BISs measure more specific interest areas such as athletics, research, culinary arts, counseling and helping, sales, and office management. The OSs relate an individual's pattern of interests to those of individuals in a wide variety of specific occupations (i.e., lawyer, psychologist, banker). The five PSSs include Work Style, Learning Environment, Leadership Style, Risk Taking/Adventure, and Teamwork Scales. T-scores on these five scales are represented on a bipolar continuum. Scores falling at the poles illustrate a strong preference for that distinctive style. T-scores of 45 or less identify one pole while scores of 55 or greater indicate the other pole. Scores falling in the middle indicate no predominate preference for one style or the other (Donnay et al., 2004). Reliability and validity information for the SII scales was reviewed in Chapter 2.

Procedure

All procedures were approved by the WSU Institutional Review Board. The SII data gathering procedure required the creation of a data disk by CPP, which was sent directly to Career Services at Washington State University (WSU). Career Services acted as a third party in an effort to comply with FERPA regulations and maintain the confidentiality of participants. The data disk provided by CPP contained all information provided in participants' SII responses (e.g., student names, demographic information, GOTs, BISs, OSs, and PSSs). CPP provided a research ID number for participants (in conjunction with each participant's name). Career Services used each individual's name to acquire the other information needed to complete the study (i.e., GPA and academic major). Career Services then provided the researcher with the de-identified data (i.e., research ID, interest test results, major, and GPA). By using a third party (i.e., Career

Services), the investigator never saw the students' names in the context of their SII results, academic major, or GPA.

Data Analysis

Hypothesis 1. Hypothesis 1 was tested by comparing participants' academic majors with their SII T-scores for the best-matched Occupational Scale (OS) scores. These analyses were conducted for 200 randomly selected participants (100 males, 100 females), in the larger database. These participants were selected at random from the total sample (*N*=501) by using the website random.org. By providing the range of numbers possible (1–501), a number was generated at random and used to designate a particular random participant in the database. This process was repeated for males and females separately until 100 female and 100 male participants were selected.

For these 200 participants, academic majors were matched to participants' OSs utilizing the McArthur classification method. This resulted in the creation of two classification groups (a) Direct hits and (b) Indirect hits. The primary investigator made classification judgments (both Direct and Indirect) by referencing several different sources. These sources included the WSU course catalog, which listed occupations associated with each major, WSU websites related to academic majors, and discussions with his dissertation advisor.

The Direct hit group was comprised of participants for whom a direct match between college major and an OS was possible. For example, a major in architecture was directly matched to the OS of architect. However, some college majors were quite broad. For example, the academic major of Business Administration could be directly matched with the OSs of banker, credit manager, financial analyst, financial manager, investments manager, marketing manager, operations manager, public administrator, and top executive. For these classification judgments, the OS with the highest score was selected as the match. The Indirect match group was comprised of participants for whom a direct one-to-one match between college major and an OS was not possible. As in previous research (Hansen & Dik, 2005), I made indirect classifications by matching college majors with two or three most closely related OSs. For example, an individual pursuing a degree in economics could be indirectly matched to the OSs of financial analyst or investments manager. In these cases, I selected the Indirect OS match with the highest score.

Both the Direct and Indirect classifications were broken down further into three subcategories (e.g., Hansen & Dik, 2005; Hansen & Lee, 2007; Hansen & Neuman, 1999; Hansen & Tan, 1992). An excellent hit consisted of a T-score greater than 45 on the corresponding OS. T-scores falling between 44 and 40 were considered a moderate hit. T-scores of 39 or below were considered a poor hit. These analyses were conducted and are reported in the Results section for all 200 randomly selected participants and for males and females separately.

Hypothesis 2. Hypothesis 2 was tested in the total sample (N= 501) by comparing the ability of the GOT, BIS, and PSS scales to predict current college major choice. Although the total number of majors sampled was 65, many of the majors were associated with small numbers of students. Therefore, the researcher and his advisor independently combined the majors into broader categories and reached consensus on 13 broader major groups (e.g., physical sciences, arts and humanities). Appendix B shows the 13 major groupings and the specific majors associated with each. The sample sizes for these larger major groups ranged from 15 to 89.

Three multiple discriminant analyses (MDA) were conducted. In each case, the criterion variable was a categorical variable indicating the college major. In three separate analyses, the predictor variables were (a) T-scores for the six GOT themes, (b) T-scores for the 30 BIS scales, and (c) T-scores for the five Personal Style Scales. MDA generates discriminant functions (weighted linear combinations) of the predictor variables, which best differentiate or predict the categorical criterion variable. The discriminant coefficients (analogous to beta weights in multiple regression) are selected by the statistical program so as to best predict or classify individuals into a college major based on their interest or Personal Style scores. The number of possible discriminant functions in each analysis is equal to the smaller of two numbers—the number of academic major groups minus 1 and the number of predictor variables. Thus, there are a maximum of six possible discriminant functions for the GOT analysis (i.e., 6 GOT predictors), 12 (13 academic major groups -1) for the BIS analysis, and five (five Personal Style predictors) for the Personal Style Scale analysis. However, it is likely that only a subset of the discriminant functions will be statistically significant based on the Wilk's lambda test. Each discriminant function, if statistically significant, indicates a combination of interest or Personal Style Scales that successfully predict or classify students into their college majors. Each discriminant function is orthogonal (i.e., uncorrelated) with each successive discriminant function, and successive functions become weaker in their ability to differentiate the college major groupings.

To quantify how well each type of scale predicts college major category, I examined the significance and size of the canonical correlations in each analysis and the percentages of correct major classifications made by the discriminant functions. The canonical correlation provides a measure of the association between the major groups and a given discriminant function, with high values indicating a stronger association between the discriminant function and the academic major groups (i.e., the function does a good job of differentiating some of the major groups). The MDA analysis also provides the percentage of students correctly classified into their major based on their discriminant function scores, which was used to compare the ability of the three types of scales to classify students into major groups. The structure coefficients represent the simple correlation between the various scales and the discriminant function. Larger structure coefficients point to interest scales or Personal Style Scales that contribute the most to predicting or classifying the college major groups differentiated by the respective discriminant functions. These MDA analyses were not conducted separately on males and females due to the limited number of male participants.

Hypothesis 3. Hypothesis 3 was tested by using Brown and Gore's (1994) C-Index to quantify the level of congruence between participants' GOT scores and the GOT associated with their declared academic major. The academic GOT was determined by looking up the corresponding college major in the *Educational Opportunities Finder* (Rosen, Holmberg, & Holland, 1997). Brown and Gore's C-index quantifies the degree of match between the first three letters of two Holland codes (i.e., C=3(X)+2(X)+(X)). The level of congruence is calculated by supplanting the Xs with either a 3 (identical match), 2 (adjacent position on hexagon), 1 (alternate position on hexagon), or a 0 (opposite position on hexagon). This calculation produces a range of scores from 1 to 18 and a theoretical mean of 9.0. Congruence scores were correlated (Pearsons *r*) with participants' cumulative GPAs. This analysis was conducted in the random sample of 200 participants and in the samples of 100 males and 100 females separately.

CHAPTER FOUR

Results

Hypothesis 1: Concurrent Validity of Occupational Scales for College Majors

In Hypothesis 1, I predicted that using the McArthur method, the Occupational Scales (OSs) of the Strong Interest Inventory (SII) will predict a participant's exact academic major (i.e., a Direct Excellent Hit) for at least 35% of the sample. The procedures used to classify hit rates for 100 men and 100 women were described in Chapter 3. Table 3 presents the concurrent validity hit rates for females and males. For readers who wish to examine the details of the major-OS matches, Appendix A shows, for each participant, college major, the hit rate classification, the selected/matched OS, the rank of the selected OS as compared to other OSs, and the T-Score for the selected/matched OS.

As seen in Table 3, Direct excellent and moderate hits for females (50%) and males (55%) were in line with expectations. In previous research the comparable percentages ranged from 36% to 62% (see Table 2 in Chapter 1). However, Direct and Indirect poor hits for females (43%) and males (38%) were higher than in previous research, where the comparable percentages ranged from 17% to 35.5% (see Table 2 in Chapter 1). Overall, these results support Hypothesis 1, as more than 35% of females and males were classified as having Direct excellent hits.

Although not involved in my hypothesis, in Appendix A I report the rank of the selected OS for each participant. These ranks show that even in cases of Direct excellent hits, there were often many other OSs for which the participants scored higher. For example, the first female in Appendix A had a Direct excellent hit for her major of accounting because she had a T-score above 45 on the accountant OS. However, she also had even higher T-scores for 62 other OSs. This provides some perspective on the results. Although Holland's typological theory would predict satisfaction for this female in the accounting profession, there were many other occupations for which satisfaction would also have been predicted.

Table 3

McArthur Hit Classifications for Female and Males

		Females (*N*=100)			Males (*N*=100)	
Hit Validity	Direct *N* / %	Indirect *N* / %	Total *N* / %	Direct *N* / %	Indirect *N* / %	Total *N* / %
Excellent	41	6	47	45	5	50
Moderate	9	1	10	10	2	12
Poor	38	5	43	28	10	38
Total	88	12	100	83	17	100

Note. Because 100 females and 100 males were studied, the values in each category equal both the number (*N*) and percentage (%) of classifications.

Hypothesis 2: Prediction of College Major Groups from GOT, BIS, and Personal Style Scales

In Hypothesis 2, I predicted that the Basic Interest Scales (BISs) of the SII would show the highest level of accuracy in predicting participant academic major followed by the GOTs and Personal Style scales. The details of the multiple discriminant analyses (MDA) used to test this hypothesis were reported in Chapter 3. Separate MDA analyses were used to test how well the GOT, BIS, and Personal Style scales could differentiate the 13 college major groupings and the percentage of participants who could be correctly classified into academic major groupings using each set of scales. Since the BIS scales were hypothesized to exhibit the greatest accuracy, I consider those results first.

BIS analysis. Table 4 presents the canonical correlations for the 12 discriminant functions relating the BIS scales as predictors of the 13 college major groupings. A Wilks' Lambda test was performed on these canonical correlations and showed that only the first seven discriminant functions were statistically significant ($p < .01$), annotated by double asterisks in the table. This means that there were seven different weighted combinations of BIS scores (i.e., discriminant functions) that were able to significantly differentiate various college major groupings. Each successive discriminant function is independent of previous functions and will be somewhat weaker in the ability to differentiate the major groups. The significant canonical correlations range from moderate to high in size, indicating that the BIS scales do a good job of differentiating the 13 major groups.

Table 4

Canonical Correlations for BIS Discriminant Functions

Function	**Canonical Correlation**
1	.62**
2	.55**
3	.47**
4	.43**
5	.40**
6	.37**
7	.34**
8	.29
9	.25
10	.23
11	.22
12	.19

Note. ** $p< .01$.

I will discuss Table 5 and 6 together, interpreting each of the seven significant discriminant functions. Table 5 (Structure Matrix) shows the correlations between each BIS and each discriminant function. BISs with high correlations, either positive or negative, with a given discriminant function best define or indicate those BISs that distinguish the major groups that are differentiated by the particular discriminant function. Table 6 shows the mean scores (group centroids) of each major group on each of the seven discriminant functions. By simultaneously examining the BISs with the high correlations on a given discriminant function and the major groups with high versus low means on the same discriminant function, we can tell which BISs are differentiating which major groups.

In Table 5, Function 1 correlated most positively with scores on the writing/communication BIS and most negatively with BISs related to math, science, and mechanics/construction. As seen in Table 6, this function best differentiated academic majors in communications and language/literature, which had high positive means on the discriminant function, versus majors in engineering/ architecture and physical science, which had large negative means. This distinction makes conceptual sense. Function 2 in Table 5 is best defined by (i.e., correlated with) BISs related to mechanics and construction, computer hardware and programming, versus BISs related to healthcare services and counseling/helping. Thus, it makes sense that this discriminant function best differentiates majors in math/computer science and engineering/architecture versus clinical health services and psychology (see Table 6).

Function 3 in Table 5 correlated positively with BISs for management, finance/investing, sales, and office manager and negatively with visual arts/design and nature/agriculture. Sensibly, mean scores for Function 3 in Table 6 were highest for the business/economics and social sciences majors and lowest for the major groups of physical science, language/literature, and natural resources/agriculture science. Function 4 in Table 5 correlated positively with the BISs of programming/information systems, computer hardware, and math, and negatively with BIS athletics. This conforms to the results in Table 6 as Function 4 best differentiated mean scores in the academic areas of math/computer science versus kinesiology.

Function 5 in Table 5 was best defined (i.e., positively correlated) by the BISs of marketing/advertising and sales. As seen in Table 6, this function differentiated majors in communications and (secondarily) business/economics, which make sense given that advertising is a sub-discipline in both communications and business. This function also differentiated, at the opposite (i.e., negative) pole, majors in arts/humanities and education/human development. Function 6 in Table 5 was best defined by (i.e., positively correlated highest with) the BISs nature/agriculture and teaching/education. This is consistent with the results in Table 6, which shows that Function 6 best differentiated majors in natural resources/agriculture science and education/human development versus clinical health sciences and math/computer science.

Finally, Function 7 in Table 5 seems best defined by BISs related to teaching/education, math, and counseling/helping versus law and politics/public speaking. In Table 6, this function was best defined by the BISs of education/human development and clinical health sciences versus math/computer science and social sciences. The interpretation or meaning of this function seems less definitive than the previous functions, perhaps because it is the weakest function that was statistically significant.

Overall, I noted meaningful conceptual links between the BISs that defined each discriminant function and the major groups that were differentiated by the corresponding functions. This is one indication that the BIS can differentiate or predict college majors to some extent. A good summary indicator of this is provided by the overall percentage of participants that could be classified into the correct major group using the BISs. Nearly half (48.1%) of participants were correctly classified. Note that with 13 major categories we would expect only 7.7% correct classifications by chance. Thus, the BISs classify participants into major groups at a much higher rate than chance.

Table 5

Structure Matrix for the BIS Discriminant Analysis

Basic Interest Scales	**Function**						
	1	**2**	**3**	**4**	**5**	**6**	**7**
Writing & Communication	**.50**	-.07	-.26	.19	.26	.07	-.06
Math	**-.48**	.25	.06	**.41**	.03	.11	**.32**
Science	**-.44**	-.06	-.30	.32	.00	.01	.02
Taxes & Accounting	-.37	.21	.32	.22	.18	.30	.18
Medical science	-.34	-.33	-.11	.16	-.01	-.04	.09
Mechanics & Construction	**-.42**	**.49**	-.11	-.06	-.16	.09	.00
Healthcare services	-.23	**-.41**	-.08	-.05	.08	.06	.10

Basic Interest Scales	**1**	**2**	**3**	**4**	**5**	**6**	**7**
Counseling & Helping	.08	**-.41**	.16	.06	-.11	.10	**.31**
Computer hardware	-.26	**.39**	.15	**.34**	**-.22**	-.04	.01
Management	-.01	.04	**.48**	-.09	.32	.12	.13
Finance & Investing	-.22	.30	**.48**	.19	.34	.17	-.20
Human Resources & Training	.16	-.07	.40	-.05	.17	.19	.11
Visual arts & Design	.13	.15	**-.34**	.01	.02	.03	.27
Performing arts	.23	-.07	-.27	.13	-.08	.04	.10
Politics & Public speaking	.21	.16	.25	.11	.19	-.09	-.25
Programming & Information systems	-.10	**.31**	.13	**.46**	-.05	.01	.04
Social sciences	.11	-.24	.22	.25	-.01	.14	-.07
Market & Advertising	.19	.20	.34	-.06	**.53**	.09	-.01
Sales	.01	.25	**.44**	.00	**.46**	.23	-.06
Nature & Agriculture	-.20	.12	**-.31**	-.04	-.03	**.50**	-.17
Teaching & Education	.26	-.20	.08	.13	-.26	**.42**	.34
Law	.08	.03	.32	.05	-.05	-.09	**.36**
Protective services	-.22	.01	.05	-.05	-.12	.09	-.24

Basic Interest Scales	**1**	**2**	**3**	**4**	**5**	**6**	**7**
Athletics	-.17	.09	.11	**-.35**	.07	-.01	-.12
Entrepreneurship	-.04	.26	.19	.06	.19	.22	-.19
Military	-.21	.15	.02	-.13	-.13	.11	-.11
Culinary arts	.16	-.06	.01	-.06	.05	.25	.06
Research	-.23	.03	-.02	.34	.16	.07	-.11
Office manager	.09	-.03	**.39**	.08	.20	.39	.18
Religion	.10	-.05	-.14	.04	-.08	.15	.11

Note. Correlations in bold indicate those BIS scales that correlated most highly in absolute value with the respective discriminant functions.

Table 6

Mean Discriminant Function Scores (i.e., Group Centroids) for each Major Group on Successive BIS Discriminant Functions

	Function						
Major Clusters	**1**	**2**	**3**	**4**	**5**	**6**	**7**
1) Physical Science	**-1.19**	-0.44	**-1.01**	.68	.28	-.10	-.37
2) Arts & Humanities	.94	.54	-.31	-.12	**-.64**	-.20	.01
3) Clinical Health Sciences	-.84	**-1.43**	-.05	-.19	.25	**-.64**	**.56**
4) Natural Resources/ Agriculture Science	-.90	-.24	**-.74**	-.46	.06	**1.02**	-.41
5) Communication	**.95**	.07	-.24	-.29	**.58**	-.27	-.01
6) Social Sciences	.13	-.23	**.51**	-.36	-.30	-.02	**-.46**
7) Languages & Literature	**1.47**	.06	**-.75**	.71	.00	.36	.03
8) Math & Computer Science	-.30	**.63**	.46	**1.64**	-.44	**-.58**	**-.49**

Major Clusters	**1**	**2**	**3**	**4**	**5**	**6**	**7**
9) Engineering & Architecture	**-1.21**	**1.71**	-.54	-.38	-.41	-.33	.48
10) Business/Economics	-.35	.45	**.66**	.18	**.44**	.27	.15
11) Kinesiology	-.54	-.12	-.17	**-.80**	-.42	.02	-.01
12) Education & Human Development	.54	-.76	.10	.32	**-.62**	**.63**	**.81**
13) Psychology	-.25	**-.77**	.30	.26	.42	-.32	-.30

GOT analysis. Table 7 presents the canonical correlations for the six discriminant functions relating the GOT scales as predictors of the 13 college major groupings. A Wilks' Lambda test was performed on these canonical correlations and showed that all but one of the discriminant functions was statistically significant. This means that there were five different weighted combinations of GOT scores (i.e., discriminant functions) that were able to significantly differentiate various college major groupings. As with the BIS scales, each successive discriminant function is independent of previous functions and will be somewhat weaker in its ability to differentiate the major groups. The GOT scales also produced canonical correlations that range from moderate to high in size (although somewhat lower than those for the BISs), indicating that the GOT scales also do a decent job of differentiating the 13 major groups. Only five of the six discriminant functions were statistically significant.

Table 7

Canonical Correlations for GOT Discriminant Functions

Function	Canonical Correlation
1	.52**
2	.46**
3	.39**
4	.31**
5	.25**
6	.13

I will discuss the results found in Table 8 and 9 together, interpreting each of the five significant discriminant functions. Table 8 (Structure Matrix) shows the correlations between each GOT scale and each discriminant function. Thus, GOT scales with high correlations, either positive or negative, with a given discriminant function best define or indicate those GOT scales that distinguish the major groups that are differentiated by the particular discriminant function. Table 9 shows the mean scores (group centroids) of each major group on each of the five discriminant functions. As with the BIS scales, by simultaneously examining the GOT scales with the high correlations on a given discriminant function and the major groups with high versus low means on the same discriminant function, we can tell which GOT scales are differentiating which major groups.

For Function 1, the two highest positively correlated GOT scales (Table 8) were Investigative and Realistic. Conceptually, this coincides with the data presented for Function 1 in Table 9, as the highest means in the positive direction were for the academic majors of engineering/architecture and physical science and the highest means in the negative direction were for communications and language/literature. For Function 2 in Table 8 the GOTs with the highest (positive) correlations were Conventional and

Enterprising. Somewhat consistent with these results, Function 2 in Table 9 produced the highest positive discriminant function means for the academic areas of business/economics and engineering/architecture and the highest negative means for the areas of clinical health sciences and education/human development. Other relatively high negative means were also observed for the areas of physical sciences, language/literature, and psychology. Function 3 in Table 8 correlated most positively with the GOT scales of Social and Conventional. Sensibly, the function in Table 9 produced the highest positive discriminant function means for the academic major of education/human development, a Social and Conventional major, and the highest means in the negative direction for arts/humanities and engineering/architecture. Function 4 in Table 8 correlated positively with the Enterprising GOT and negatively with the Realistic GOT. As seen in Table 9 this function primarily differentiates the kinesiology majors, who were associated with the negative (Realistic) pole of the function, from other majors. Finally, Function 5 in Table 8 is best defined by the GOTs of Conventional and Artistic. In Table 9, Function 5 best differentiated the academic areas of languages/literature and math/computer science from psychology. The interpretability of this function is less clear, probably consistent with its modest canonical correlation (.25).

Overall, these results indicate that the GOT scales have the ability to differentiate or predict college majors to some degree. The GOTs predicted college major group better than chance, with nearly a third (31.7%) of participants being correctly placed in the correct major group. However, consistent with Hypothesis 2, the GOTs classified participants less accurately than did the more specific BIS scales.

Table 8

Structure Matrix for the GOT Discriminant Analysis

General Occupational Themes	**Function**				
	1 (I & R)	**2 (C & E)**	**3 (C & S)**	**4 (E VS. R)**	**5 (C & A)**
Investigative	**.65**	-.33	.01	.26	.28
Conventional	.18	**.41**	**.48**	.17	**.69**
Artistic	-.37	-.24	-.37	.06	**.41**
Realistic	**.51**	.35	-.13	**-.35**	.13
Social	-.31	-.32	**.55**	-.21	.08
Enterprising	-.24	**.59**	.31	**.37**	-.06

Note. The most highly related GOT themes are noted in parentheses for each function (column).

Table 9

Mean Discriminant Function Scores (i.e., Group Centroids) for each Major Group on Successive GOT Discriminant Functions

	Function				
Major Clusters	**1**	**2**	**3**	**4**	**5**
1) Physical Science	**1.14**	**-.71**	-.37	.46	.02
2) Arts & Humanities	-.51	.06	**-.81**	-.20	.16
3) Clinical Health Sciences	.57	**-.93**	.25	**.39**	-.21
4) Natural Resources & Agriculture Science	.59	-.08	-.26	-.30	-.12
5) Communication	**-.84**	.15	-.21	.25	-.26
6) Social Sciences	-.11	.20	.21	-.20	.00

Major Clusters	**1**	**2**	**3**	**4**	**5**
7) Languages & Literature	**-.71**	**-.49**	-.50	.15	**.58**
8) Math & Computer Science	.87	.17	.06	.24	**.54**
9) Engineering & Architecture	**1.04**	**.59**	**-.65**	-.37	-.06
10) Business & Economics	.16	**.66**	.44	.23	.10
11) Kinesiology	.40	-.10	.12	**-.92**	-.24
12) Education & Human Development	-.52	**-.92**	**.73**	-.45	.38
13) Psychology	-.19	**-.56**	.23	-.05	**-.52**

PSS analysis. Table 10 presents the canonical correlations for the five discriminant functions derived with the PSS scales as predictors of the 13 college major groupings. The canonical correlations are only moderate in size, and only the first two discriminant functions were statistically significant and thus able to differentiate various college major groupings.

Table 10

Canonical Correlations for PSS Discriminant Functions

Function	Canonical Correlation
1	.49**
2	.39**
3	.23
4	.15
5	.07

Function 1 in Table 11 was best defined by the Work Style PSS and seems to define a people-oriented dimension (i.e., working with others rather than independently). Thus, it makes sense that Function 1 in Table 12 differentiates the people-oriented education/human development majors from the things oriented majors of engineering/architecture and math/computer science. Function 2 in Table 11 is best defined by the Learning Environment PSS (inversely), which suggests that this dimension identifies individuals with more applied or practical interests rather than theoretical or abstract interests. Thus, it makes sense that Function 2 in Table 12 best differentiates kinesiology majors from majors in languages/literature and math/computer science. In general, nearly one quarter (24.8%) of participants were correctly classified into the proper major groups using the PSSs. This is greater than chance, but less than the percentage of correct predictions by the BISs and GOTs, probably because PSSs are not as directly related to major choice.

Table 11

Structure Matrix for the PSS Discriminant Analysis

Personal Style Scale	**Function**	
	1	**2**
Work style	**.87**	.44
Learning environment	.38	**-.67**
Leadership	.30	.14
Risk taking	-.37	.28
Team orientation	.03	.46

Table 12

Mean Discriminant Function Scores (i.e., Group Centroids) for each Major Group on Successive PSS Discriminant Functions

	Function	
Major Clusters	**1**	**2**
1) Physical Science	-.79	-.44
2) Arts & Humanities	.10	-.57
3) Clinical Health Sciences	-.09	.08
4) Natural Resources & Agriculture Science	-.42	.10
5) Communication	.58	.00
6) Social Sciences	.03	.26
7) Languages & Literature	.68	**-1.17**
8) Math & Computer Science	**-.90**	**-.69**
9) Engineering & Architecture	**-1.37**	-.17
10) Business/Economics	-.14	.38
11) Kinesiology	-.28	**.75**
12) Education & Human Development	**1.02**	.23
13) Psychology	.35	.00

In conclusion, consistent with Hypothesis 2, the BIS scales contributed the most to predicting or classifying college majors followed by the GOT and PSS scales. The BIS scales had the most statistically significant discriminant functions (7), the two highest canonical correlations (see Table 4, .62, .55) and the highest percentage (48%) of correctly placed participants in the major groups. Although less precise, the GOT scales were also effective in differentiating college major groups. Perhaps most notable was the proportion of significant canonical correlations for the GOT scales relative to the BIS and PSS scales, although the BIS scales classified more participants' majors correctly. Least useful were the PSS scales, which had the lowest canonical correlations, and showed the worst ability to correctly classify participants into major groups.

Hypothesis 3: The Congruence-Achievement Hypothesis

In Hypothesis 3 I predicted that greater GOT congruence between individuals' interest scores and their academic majors would be associated with greater cumulative GPAs (i.e., the congruence-achievement hypothesis). As described in Chapter 3, I tested this hypothesis by computing Brown and Gore's (1994) C-index between participants' three-letter Holland codes and the code for their college majors, then correlating the C-indices with cumulative GPAs. I converted each participant's declared college major to a three-letter Holland code type (i.e., RIASEC typology) using the Educational Opportunities Finder. This was done for the same randomly selected 100 female and 100 male participants used in the McArthur classifications for Hypothesis 1. The GOT codes used and the C-index computations for each participant are shown in Appendix C.

Female C-index scores ranged from 3 to 18, male scores ranged from 1 to18. The females had a higher average C-index (M = 11.34; SD = 3.71) than males (M = 9.9; SD = 3.71). Females also had a slightly higher GPA (M = 3.09; SD = .54) than males (M = 2.92; SD = .49). Independent sample t tests revealed statistically reliable differences between males and females on the C-index variable $t[198] = 2.80$, $p < .05$) and on GPA $t[198] = 2.43$, $p < .05$.

Results for the congruence-GPA correlation in the total sample were marginally significant ($r = .13$, $p < .07$). However, the size of this correlation is of little practical importance as less than 2% of the variance in GPAs was explained by congruence. The congruence-GPA correlations in the female sample (*r* = .08, *p* > .05) and in the male sample (*r* = .12, *p* > .05) were smaller and not statistically significant Overall, these results provide little support for the congruence-achievement hypothesis (i.e., Hypothesis 3), at least when achievement is operationalized as cumulative GPA.

CHAPTER 5

Discussion

The purpose of this study was to investigate the way counselors and researchers assess and measure vocational interests and better understand how these interests align with undergraduate academic majors. There were three areas of focus: (a) examining the concurrent validity hit rates for the OSs utilizing the McArthur method; (b) analyzing which scales (i.e., GOTs, BISs and PSSs) on the SII are more effective at differentiating and predicting concurrent college majors, and (c) exploring how well congruence between individuals' Holland personality types and the types associated with their declared academic majors predicts level of achievement (i.e. GPA). The results of this study could be used to enhance service delivery to clients who remain undecided about their academic major, inform future empirical investigations and increase retention rates at universities.

SII results were obtained from participants and compared to their declared academic major and GPA. Results of this study shed light on how an individual's measured vocational interests related to undergraduate academic majors and the extent of congruence between measured interests and achievement. Findings support the ability of the SII to accurately predict concurrent majors at the undergraduate level. Specifically, the first hypothesis stating that the OSs of the SII will predict a participant's exact academic major (Direct Excellent Hit) for at least 35% of the sample was supported. The second hypothesis that the BISs of the SII will show the highest level of accuracy in predicting participant academic majors followed by the GOTs and PSSs was also supported. Finally, the last hypothesis, testing that the congruence between individuals'

GOT scores and their academic majors will be associated with greater cumulative GPAs, was not supported. The discussion is organized into the following sections: Concurrent Validity of OSs for College Majors; Prediction of College Major Groups from the GOT, BIS, and PSS; The Congruence-Achievement Hypothesis; Strengths and Limitations of the Current Study; Areas of Future Research; and Conclusions.

Concurrent Validity of Occupational Scales for College Majors

Results indicate that the percentage of participants who scored 40 or greater on the OS that matched their current academic major was 50% for females and 55% for males. These values are within the range of concurrent validity hit rate percentages found in previous research (Hansen & Swanson, 1983; Hansen & Tan, 1992; Hansen & Neuman, 1999) and support hypothesis one. As previous research has pointed out (Hansen & Dik, 2005; Hansen & Sackett, 1993), hit rates have little interpretative value unless they are compared to chance hit rates. Essentially, the question being asked is: what is the probability that an individual will have an OS score equal to or greater than 40? Chance hit rates were calculated using the method proposed by Hansen and Sackett (1993). This method of calculating chance hit rates required recording the rank of the cut off score, dividing it by the total possible number of OSs (X/244) and then computing the average of this value for female and males. For example, for a participant with a T-score of 40 at rank 80 of the OSs, 80/244 yields a 32% chance of getting a T-score above 40 (i.e., excellent/moderate hit). For my study chance hit rates were computed as 29.4% for females and 27.3% for males, well below the hit rate percentages reported for moderate and excellent hits in my study. This is comparable to previous research

(Hansen & Dik, 2005; Hansen & Sackett, 1993) and provides further evidence in the ability of the OSs to predict concurrent academic majors at the undergraduate level.

Although the OSs demonstrated their potential in predicting concurrent academic majors, this study raises questions about their level of precision. The results revealed that even in cases of a Direct excellent hit, there were often many other OSs for which the participant scored higher. For example, a female participant majoring in social sciences was directly matched with the OS of Social Science Teacher (SST), which was ranked 76. Therefore, this female participant could have received a Direct excellent match on 75 other OSs because the SST T-score was greater than 45. Results such as these are indicative of individuals with many interests. In general, the results of this section indicate that participants had many interests illustrated by their high T-score values. This finding could have significant implications in a career-counseling situation when attempting to narrow down interests and provide meaningful interpretation to test results. This could also influence future research, which might overestimate the predictive power of the SII. Lastly, this finding could have significant implications for universities and colleges attempting to increase student retention rates. Preliminary evidence (Hannah, 2007) indicates that students are less likely to remain enrolled in classes if they remain “undecided” in declaring an academic major. This also highlights the need for future research in the area of vocational interests as there has been no other mention of this in previous investigations. That is, researchers have reported hit rates associated with matching OS scales without reporting the number of OSs for which participants actually scored higher.

The last area to be discussed in this section is female and male poor hit classifications (43% and 38%, respectively); the percentages are higher than those reported in previous research. For example, Hansen and Tan (1992) reported lower Poor Direct and Indirect hit rates for undergraduate females (20.5%) as well as males (17%). However, in a more recent study, Hansen and Neuman (1999) reported poor hits more consistent with my study, that is, 35.5% for females and 31.8% for males. Taking a closer look at the Direct poor hits in my study revealed that more than half of females and males were in majors that had a Direct match between an OS and their academic major (e.g., architect, biologist, nursing, sociologist). Analyzing participant GPAs that received poor hits showed that they had only slightly lower GPAs compared to participants that received excellent or moderate classifications. Notably, of the 17 female and male psychology majors (17) all but two received a poor hit. Previous investigations (Hansen & Tan, 1992) have illustrated how participants that received a poor hit were enrolled in academic majors that were inconsistent with their larger vocational pursuits after graduation; this could be one possible explanation for the higher poor hit rates in the present study and may be indicative of individuals that have many different interests. For, example it could be argued from the results found here that psychology majors are in general unlikely to pursue a career as a psychologist.

Prediction of College Major Groups from GOT, BIS and PSS

Previous research on the ability of the GOTs, BISs and PSSs to accurately predict or differentiate college majors has been relatively sparse. There have been few studies (Gasser et. al.; 2007; Ralston, Borgen, Rottinghaus, & Donnay 2004) conducted that have explored the ability of these scales (GOTs, BISs and PSSs) to differentiate between different college majors. In the current study hypothesis two was supported because the BISs differentiated between college majors the best, followed by the GOTs and PSSs. Similar to the analysis conducted on the OSs, it is important to compare these hit rates to their probability of correct classifications by chance. The BISs had hit rates six times greater than chance, the GOTs four times greater and the PSSs three times greater. These results attest to the differentiating power that these various scales can provide. Moreover, these results are very similar and firmly supported by Gasser et al.'s (2007) and Ralston et al.'s (2004) investigations.

There are several possible explanations as to why the BISs are better able to differentiate between majors. The first hinges on the fact that there are considerably more scales within the BISs (30) compared to the GOTs (6) and the PSSs (5). The second relates to the fact that the BISs have been recently refined in the latest revision of the SII used for this study and might be more in line with the contemporary nature of specific academic majors (i.e., those related to technology). Lastly, the BISs were constructed as homogeneous scales and focus on a specific interest domain. For example, the Counseling and Helping BIS contains items such as "working in a program for the disadvantaged," "helping others overcome difficulties," "psychology," "social work" and "contributing to charities"; these items have good face validity because responses provide knowledge about the individual's feelings toward counseling and helping activities. Thus, it is likely that individuals who positively endorse these items related to counseling and helping are more likely to pursue an academic major that supports these values or lifestyle activities.

The results of this study showed that the GOTs were less effective at differentiating between academic majors than the BISs. The GOTs are broader than the BISs and account for several areas related to vocational interests. These areas include typical work activities, potential competencies, self-concept/values, environments, typical hobbies and sample occupations. In general the GOTs lack the level of occupational specificity of the BISs and are more useful for guiding the overall vocational or academic picture. Therefore, it is not surprising that the GOTs show less differentiating power.

The scales illustrating the weakest differentiating power are the PSSs. Conceptually, it makes sense that the PSSs are less accurate in predicting academic majors because half their content is more related to specific activities than specific careers. For example, the PSS of Leadership Style contains items such as “heading a civic improvement program,” “meeting and directing people,” and “put drive into an organization.” The take-home message of this study is that the BISs’ specific interest dimensions are more clearly linked toward specific career pathways and their related academic majors. Therefore, when results on the SII indicate a wide range of interests, taking the time to carefully analyze BIS scores might be helpful in narrowing interests and guiding an individual toward a specific academic/career path.

The Congruence-Achievement Hypothesis

For more than 30 years researchers have been exploring the relationship between congruence and achievement. Overall, there has been little evidence supporting or negating the validity of this hypothesis. Although GPA has frequently been used as a measure of achievement, other studies have also used academic persistence (Bruch &

Krieshok, 1981) and annual incomes (Schwartz et al. 1986) in an attempt to link congruence to achievement. The results of this current study appear to fall well within the general framework of results reported for investigations concerning the congruence achievement hypothesis. Specifically, the results of this study showed only a modest and marginally significant correlation between GOT codes and level of achievement as measured by GPA, and only in the total (combined-sex) sample. Indeed, these results are far from definitive and it might be best to conclude that there was no support for the congruence-achievement hypothesis in this study.

The modest results in this current study could be related to the overall high level of interests displayed in the sample. Perhaps this is best illustrated by examining the rank of matched OSs to academic majors. As previously pointed out, individuals that display high overall interests have a greater ability to receive an excellent or moderate hit. This concurs with previous research (Tracey & Robbins, 2006) exhibiting that individuals who display higher overall interests also demonstrate higher interest flexibility and lower levels of congruence. Another possible factor moderating congruence in this dataset is the fact that GPAs were recorded across all academic levels (i.e., freshman to college graduate). It is possible that levels of congruence could have been impacted if all GPAs would have been recorded after graduation. Finally, the fact that females averaged higher than males in both congruence and GPA suggests that the marginally significant and modest correlation in the total sample might be due to gender differences on these two variables.

Strengths and Limitations of Current Study

Several strengths can be identified when analyzing the results of the present study. First, this is the only known study to have examined the concurrent validity hit rates for all scales on the most recent version of the SII. Of the previously reviewed empirical investigations concerning concurrent validity hit rates, few, if any, have mentioned or analyzed the rank associated with each individual's matched OS. Second, this study makes significant contributions to vocational interest testing by explicitly describing the way Direct and Indirect matches were generated. Third, this study sets itself apart from previous research by using more objective resources (i.e., WSU course catalog, websites pertaining to specific academic majors, having more than one judge making classifications) to make classification judgments. Previous research regarding Direct and Indirect hit classifications has often relied heavily upon subjective classification judgments by the investigator(s). All too often these empirical investigations have been void of the specific methods employed in classifications making replication difficult at best.

Along with the strengths of the study, several limitations can also be found in the sample. First, there were significantly more females than males in the total sample resulting in an inability to assess any possible differences related to gender on hypothesis two. Second, due to the limited sample size and large variety of academic majors, the small number of participants in some of the academic categories (i.e., Computer science, n = 5) required grouping majors together into more general categories (e.g., construction management placed into the business/economics category). This limitation made it impossible to analyze how well specific BIS scales differentiate specific academic majors, for example, how well the BIS of construction management differentiates construction management majors from other academic disciplines. Third, regarding the results for hypothesis one, some skepticism may be expressed as to how well the OSs predict academic majors if a participant could receive a Direct excellent hit for an OS ranked 76. Fourth, results for the congruence achievement hypothesis may have been influenced by the fact that GPAs were not all recorded at the same time (i.e. post graduation). Finally, the researcher did not have available information on how the SII results were used during the students' tenure at the university. It is likely that some SII results were used in vocational counseling to assist the students in college major choice. If so, hit rates would presumably be higher than they would be had students' SII results not informed their choices of major. This limitation has characterized most previous studies of SII validity, however, so the results of the present study are probably still comparable with the results of earlier studies.

Recommendations for Future Research

The strengths and weaknesses of the current study lend insight into some of the areas for future research; specifically, attempts should be made to generate a larger sample set that has a balanced body of male and female participants. Future researchers using the McArthur method should consider increasing the cut off scores for classification categories (i.e. excellent, moderate, poor). It is likely that increasing cut off scores would reduce excellent and moderate hit rate percentages. However, these results might be more meaningful and have greater applicability if cut off scores were above mean OS T-scores (i.e., > 50) scores reported for the SII. Replicating this study on a different undergraduate population while employing a similar methodology on all scales of the most recent version of the SII with academic majors serving as the criterion would be very helpful. A follow-up study using the same participants might also be warranted in an effort to further understand the ability of the SII to predict occupations. It would be interesting to see if the participants used in this sample that had higher OSs (Direct or Indirect) were more or less likely to pursue a career within their academic major as research in this area has been relatively sparse. Results could have significant clinical and empirical implications as they could be used to further understand important individual career developmental stages. Future studies should also attempt to evaluate the concurrent and predictive validity for the SII within minority and underserved populations. Finally, it would be informative to collect information on how the SII results were actually used by students and how direct a role their scores played in their college major choices.

Conclusion

This study identified several areas of vocational interest testing with the SII that warranted further investigation. The theoretical foundation on which the SII is based (Holland's Typological Theory) was discussed and related to its ability to predict academic majors at the undergraduate level. The most commonly used interest inventories from the past 60 years were explored. Next, the validity of the SII was examined in great detail encompassing empirical investigations over the past 70 years. Specifically, the concurrent and predictive validity of the SII was broken down by the criterion used (i.e., academic major or occupational choice) to validate its ability to predict academic majors and occupations. This method allowed for a better understanding as to how empirical investigations concerning the validity of the SII have evolved over this time frame. It also resulted in identifying areas where further research concerning the validity of the SII and the congruence achievement hypothesis was warranted. These gaps in the research relate specifically to the three hypotheses investigated in this study, which were analyzed and generally supported. The clinical, empirical and practical implications were discussed, and the areas of strength and weakness were identified. Although, this current work provides additional knowledge about how interest testing relates to predicting academic majors, there are still several aspects that deserve attention. Ultimately, the goal is to have the best understanding as to how vocational and academic interests intersect with an individual's passion and how this passion relates to academic and vocational opportunities. Hopefully, studies like this will bring us one step closer to understanding how we can help others achieve academic and career successes.

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Appendix A

McArthur Hit Rates

Females

College Major	Hit Classification	Selected/Matched OS	Rank	T-Score
Accounting	Direct, Excellent	Accountant	63	47.63
Animal Science	Direct, Excellent	Farmer Rancher	5	58.9
Animal Science	Direct, Excellent	Veterinarian	16	45.53
Animal Science	Direct, Moderate	Farmer Rancher	12	44.63
Apparel Merchandising	Direct, Excellent	Buyer	6	67.63
Biology	Direct, Poor	Biologist	119	39.19
Biology	Direct, Poor	Biologist	103	37.6
Biology	Direct, Poor	Biologist	160	29.08
Biology	Direct, Poor	Biologist	104	34.01
Business Administration	Direct, Excellent	Operations Manager	2	71.35
Business Administration	Direct, Excellent	Operations Manager	2	67.13
Business Administration	Direct, Excellent	Credit Manager	1	67.82
Business Administration	Direct, Excellent	Operations Manager	46	51.65
Business Administration	Direct, Excellent	Banker	6	57.33
Business Administration	Direct, Excellent	Top Executive	17	49.32
Business Administration	Direct, Excellent	Operations Manager	1	61.5
Communication	Direct, Excellent	Broadcast Journalist	8	53.93
Communication	Direct, Excellent	Broadcast Journalist	64	48.98
Communication	Direct, Poor	Broadcast Journalist	81	33.04
Communication	Direct, Excellent	Broadcast Journalist	20	56.41
Communication	Direct, Excellent	Reporter	22	52.81
Communication	Direct, moderate	Broadcast Journalist	71	42.81
Communication	Direct, Excellent	Broadcast Journalist	32	50.22
Communication	Direct, Poor	Broadcast Journalist	101	31.68
Communication	Direct, Excellent	Broadcast Journalist	23	45.28
Communication	Direct, Excellent	Broadcast Journalist	33	51.46
Communication	Direct, Excellent	Broadcast Journalist	3	61.35
Communication	Direct, Poor	Broadcast Journalist	155	34.15
Communication	Direct, Poor	Broadcast Journalist	111	34.15
Criminal Justice	Direct, Poor	Law Enforcement Officer	83	37.4
Education	Direct, Excellent	Elementary School Teacher	1	62.61
Education	Direct, Poor	Elementary School Teacher	93	39.94
Education	Direct, Excellent	Elementary School Teacher	22	62.61
Education	Direct, Excellent	Elementary School Teacher	1	72.77
Education	Direct, Excellent	College Instructor	14	50.72
Education	Direct, Poor	College Instructor	65	35.64
English	Direct, Poor	English Teacher	139	29.23
English	Direct, Moderate	English Teacher	44	44.87
English	Direct, Excellent	English Teacher	58	50.96
English	Direct, Poor	English Teacher	182	20.19

College Major	Hit Classification	Selected/Matched OS	Rank	T-Score
Fine Arts	Direct, Excellent	Art Teacher	6	62.61
Fine Arts	Direct, Poor	Artist	67	39.45
Fine Arts	Direct, Excellent	Artist	13	56.1
Fine Arts	Direct, Excellent	Art Teacher	25	46.86
Foreign Languages and Cultures	Direct, Moderate	Foreign Lang Teacher	80	40.2
German	Direct, Excellent	Foreign Lang Teacher	9	48
History	Indirect, Excellent	Social Science Teacher	27	46.32
History	Indirect, Poor	Social Science Teacher	76	32.34
Hospitality Business Management	Direct, Excellent	Restaurant Manager	58	47.82
Human Development	Indirect, Excellent	Nursing Home Admin	18	51.8
Human Development	Indirect, Excellent	Nursing Home Admin	19	62.64
Human Development	Indirect, Excellent	Nursing Home Admin	16	53.61
Humanities	Indirect, Poor	Social Worker	109	32.68
Humanities	Indirect, Poor	Social Worker	92	36.37
Interior Design	Direct, Moderate	Interior Design	34	41.34
Interior Design	Direct, Moderate	Interior Design	39	41.13
International Business	Direct, Excellent	Financial Analyst	10	47.08
Math	Direct, Moderate	Math Teacher	50	41.5
Movement Studies	Direct, Excellent	Physical Ed Teacher	42	46.69
Movement Studies	Direct, Excellent	Physical Ed Teacher	12	56.94
Movement Studies	Direct, Poor	Physical Ed Teacher	127	20.04
Natural Resource Sciences	Indirect, Poor	Geographer	198	16.95
Natural Sciences	Indirect, Poor	Geographer	111	39.72
Neuro Science	Direct, Moderate	Biologist	22	42.72
Nursing	Direct, Poor	Registered Nurse	91	33.97
Nursing	Direct, Excellent	Registered Nurse	22	45.94
Nursing	Direct, Excellent	Licensed Nurse	13	52.61
Nursing	Direct, Moderate	Registered Nurse	75	43.94
Nursing	Direct, Excellent	Registered Nurse	10	55.51
Nursing	Direct, Excellent	Registered Nurse	15	53.1
Pharmacy	Direct, Poor	Pharmacist	69	35.14
Political Science	Direct, Excellent	Elected Public Official	30	58.81
Political Science	Indirect, Moderate	Attorney	38	43.65
Pre Med	Direct, Excellent	Physician	6	62.01
Pre Med	Direct, Poor	Registered Nurse	61	36.36
Psychology	Direct, Poor	Psychologist	216	10.3
Psychology	Direct, Poor	Psychologist	142	24.72
Psychology	Direct, Poor	Psychologist	200	10.3
Psychology	Direct, Poor	Psychologist	135	31.93
Psychology	Direct, Poor	Psychologist	165	21.45
Psychology	Direct, Poor	Psychologist	184	22.92
Psychology	Direct, Poor	Psychologist	229	6.7
Psychology	Direct, Poor	Psychologist	139	22.92
Psychology	Direct, Poor	Psychologist	233	10.3
Psychology	Direct, Poor	Psychologist	76	37.34
Social Sciences	Direct, Poor	Social Science Teacher	217	18.37

College Major	Hit Classification	Selected/Matched OS	Rank	T-Score
Social Sciences	Direct, Excellent	Social Science Teacher	76	47.59
Social Sciences	Direct, Poor	Social Science Teacher	205	8.21
Social Sciences	Direct, Poor	Social Science Teacher	87	39.96
Sociology	Direct, Poor	Sociologist	215	14.34
Sociology	Direct, Poor	Sociologist	229	1.51
Sociology	Direct, Poor	Sociologist	214	5.89
Sociology	Direct, Poor	Sociologist	231	4.75
Sociology	Direct, Poor	Sociologist	190	20.7
Sociology	Direct, Excellent	Sociologist	6	61.17
Soil Science	Indirect, Excellent	Vocational Ag Teacher	37	45.98
Speech and Hearing Science	Direct, Poor	Speech Pathologist	118	37.37
Speech and Hearing Science	Direct, Poor	Speech Pathologist	73	37.37
Womens Studies	Indirect, Excellent	Social Worker	22	51.12
Zoology	Direct, Excellent	Veterinarian	3	58.37

Males

College Major	Hit Classification	Selected/Matched OS	Rank	T-Score
Architecture	Direct, Excellent	Architect	16	52.2
Architecture	Direct, Poor	Architect	83	30.13
Architecture	Direct, Poor	Architect	42	36.06
Athletic Training	Direct, Poor	Physical Education Teacher	49	39.35
Athletic Training	Direct, Excellent	Physical Education Teacher	32	49.99
Biology	Direct, Poor	Biologist	222	13.08
Biology	Direct, Moderate	Biologist	22	43.3
Biology	Direct, Poor	Biologist	144	27.58
Business Administration	Direct, Excellent	Marketing Manager	21	55.87
Business Administration	Direct, Excellent	Banker	2	69.22
Business Administration	Direct, Excellent	Credit Manager	3	69.76
Business Administration	Direct, Excellent	Financial Manager	18	51.79
Business Administration	Direct, Excellent	Credit Manager	17	62.88
Business Administration	Direct, Excellent	Top Executive	42	49.22
Business Administration	Direct, Moderate	Top Executive	60	42.33
Business Administration	Direct, Excellent	Credit Manager	17	60.12
Business Administration	Direct, Excellent	Banker	15	49.24
Business Administration	Direct, Excellent	Banker	23	45.24
Business Administration	Direct, Excellent	Banker	19	46.57
Business Administration	Direct, Excellent	Financial Manager	2	60.66
Business Administration	Direct, Excellent	Banker	30	59.89
Business Administration	Direct, Excellent	Credit Manager	1	63.38
Business Administration	Direct, Excellent	Credit Manager	29	51.86
Business Administration	Direct, Excellent	Operations Manager	7	60.17
Business Administration	Direct, Excellent	Credit Manager	5	60.12
Chemistry	Direct, Moderate	Chemist	85	40.37
Civil Engineering	Direct, Moderate	Engineer	45	42.82

College Major	Hit Classification	Selected/Matched OS	Rank	T-Score
Civil Engineering	Direct, Excellent	Engineer	18	49.47
Civil Engineering	Direct, Poor	Engineer	172	24.52
Communication	Direct, Poor	Broadcast Journalist	108	36.44
Communication	Direct, Poor	Broadcast Journalist	79	36.44
Communication	Direct, Excellent	Broadcast Journalist	28	56.91
Communication	Direct, Moderate	Broadcast Journalist	62	43.27
Communication	Direct, Excellent	Broadcast Journalist	32	46.68
Communication	Direct, Excellent	Broadcast Journalist	10	46.68
Communication	Direct, Moderate	Reporter	50	41.09
Communication	Direct, Moderate	Reporter	35	43.39
Communication	Direct, Excellent	Broadcast Journalist	7	51.79
Communication	Direct, Excellent	Broadcast Journalist	1	65.44
Comparative Ethnic Studies	Indirect, Poor	Sociologist	241	4.39
Computer Engineering	Direct, Poor	Computer System Analyst	109	38.48
Computer Science	Direct, Excellent	Computer System Analyst	21	47.34
Computer Science	Direct, Excellent	Computer System Analyst	1	62.82
Criminal Justice	Direct, Excellent	Law Enforcement	21	46.02
Criminal Justice	Direct, Excellent	Law Enforcement	1	78.23
Criminal Justice	Direct, Excellent	Law Enforcement Officer	5	55.24
Criminal Justice	Direct, Excellent	Law Enforcement Officer	33	50.62
Criminal Justice	Direct, Poor	Law Enforcement Officer	82	36.58
Digital Tech and Culture	Indirect, Poor	Graphic Designer	109	26.68
Digital Tech and Culture	Indirect, Poor	Graphic Designer	129	28.3
Economics	Indirect, Moderate	Financial Analyst	98	41.86
Economics	Indirect, Excellent	Financial Analyst	24	51.83
Economics	Indirect, Excellent	Financial Analyst	3	61.8
Education	Direct, Excellent	Elementary School Teacher	2	64.19
Electrical Engineering	Direct, Poor	Engineer	156	29.51
English	Direct, Excellent	English Teacher	31	53
English	Direct, Poor	English Teacher	87	30.76
Environmental Science	Indirect, Poor	Geographer	179	18.63
Environmental Science	Indirect, Poor	Geographer	164	24.89
Finance	Direct, Excellent	Financial Analyst	35	45.85
Fine Arts	Direct, Excellent	Art Teacher	5	53.74
Fine Arts	Direct, Moderate	Art Teacher	27	42.57
Fine Arts	Direct, Excellent	Artist	8	48.75
Geology	Direct, Excellent	Geologist	9	46.41
German	Direct, Poor	Foreign Language Teacher	234	6.67
History	Indirect, Poor	Social Science Teacher	99	31.08
Hospitality Business Management	Direct, Moderate	Restaurant Manager	70	42.6
Hospitality Business Management	Direct, Excellent	Restaurant Manager	13	61.91
Human Development	Indirect, Poor	Nursing Home Admin	97	34.19
International Business	Direct, Excellent	Banker	6	54.57
Landscape Architecture	Direct, Poor	Architect	161	18.24
Landscape Architecture	Direct, Poor	Architect	143	32.15
Management Information Systems	Direct, Excellent	Computer IS Manager	39	52.38

College Major	Hit Classification	Selected/Matched OS	Rank	T-Score
Management Operations	Direct, Moderate	Operations Manager	46	41.27
Marketing	Direct, Poor	Marketing Manager	120	29.79
Math	Direct, Excellent	Mathematician	13	51.52
Mechanical Engineering	Direct, Excellent	Engineer	15	49.47
Mechanical Engineering	Direct, Excellent	Engineer	52	54.46
Movement Studies	Direct, Poor	Physical Education Teacher	43	39.35
Natural Resource Sciences	Indirect, Poor	Geographer	220	18.63
Political Science	Indirect, Excellent	Attorney	2	61.14
Political Science	Indirect, Excellent	Social Science Teacher	11	57.04
Political Science	Indirect, Poor	Attorney	200	7.41
Political Science	Indirect, Moderate	Elected Public Official	80	42.4
Political Science	Indirect, Poor	Attorney	42	37.42
Political Science	Indirect, Excellent	Elected Public Official	13	47.09
Pre med/ Pre Dental	Direct, Excellent	Dentist	30	50.76
Psychology	Direct, Poor	Psychologist	181	18.3
Psychology	Direct, Excellent	Psychologist	24	49.54
Psychology	Direct, Poor	Psychologist	197	21.6
Psychology	Direct, Excellent	Psychologist	35	46.23
Psychology	Direct, Poor	Psychologist	114	31.47
Psychology	Direct, Poor	Psychologist	175	19.95
Psychology	Direct, Poor	Psychologist	183	21.6
Social Sciences	Direct, Poor	Social Science Teacher	108	32.31
Social Sciences	Direct, Poor	Social Science Teacher	192	12.53
Social Sciences	Direct, Poor	Social Science Teacher	153	28.6
Sociology	Direct, Poor	Sociologist	225	2.29
Sociology	Direct, Poor	Sociologist	225	6.49
Zoology	Direct, Poor	Veterinarian	125	31.04

Appendix B

Major Classification Judgments

I. Physical Science (30)	**II. Arts and Humanities (35)**	**IV. Clinical health Sciences (28)**	**V. Natural Resource/Agricultural Science (25)**
Biology (18)	Fine arts (8)	Nursing (15)	Agriculture Food Systems (2)
Chemistry (1)	History (12)	Pharmacy (4)	Soil science (1)
Physical science (2)	Humanities (3)	Pre-med (9)	Horticulture (2)
Physics (1)	Music (4)		Animal science (8)
Zoology (4)	Philosophy (3)		Food science (3)
Genetics/cell biology (1)	Theater (1)		Geology (1)
Microbiology (1)	Digital technology and culture (4)		Environmental science (2)
Neuroscience (2)			Natural resources (6)

V. Communication (75)	**VI. Social science (76)**	**VII. Literature/languages (26)**	**VIII. Math/computer science (15)**
Communication (62)	Anthropology (2)	English (17)	Management information systems (7)
Speech/hearing science (13)	Comparative ethnic studies (6)	Foreign languages and culture (4)	Computer science (5)
	Social sciences (11)	German (2)	Math (3)
	Sociology (24)	Spanish (2)	
	Women's studies (1)	Chinese (1)	
	Political science (15)		
	Pre-law (1)		
	Criminal Justice (16)		

IX. Engineering/architecture (27)	**X. Business/Economics (89)**	**XI. Kinesiology (19)**	**XII. Education/human development (27)**
Architecture (7)	Business administration (54)	Movement studies (13)	Education (15)
Civil engineering (6)	Accounting (15)	Athletic training (3)	Human development (12)

Mechanical engineering (6)	Economics (8)	Kinesiology (2)
Electrical engineering (3)	Merchandising (3)	Health/fitness (1)
Interior design (3)	Marketing (3)	
Landscape architecture (2)	Hospitality management (3)	
	International business (2)	
	Construction management (1)	
XIII. Psychology (28)		

Appendix C

C-Index Calculations

Females

RIASEC Participant Code	Major Used	C-Index computation	C-Index totals	RIASEC Major Code
ECI	Accounting	6+4+3	13	CEI
ERC	Animal Science	3+4+2	9	RIE
IRS	Animal Science	6+4+2	12	RIE
IRA	Animal Science	6+4+1	11	RIE
EAC	Apparel Merchandising	9+4+0	13	ESA
IEC	Biology	9+2+2	13	IAR
CIS	Biology	3+4+0	7	IAR
ISE	Biology	9+4+1	14	IAR
IAR	Biology	9+6+3	18	IAR
ECS	Business Administration	9+4+3	16	ERS
ECS	Business Administration	9+4+3	16	ERS
ECS	Business Administration	9+4+3	16	ERS
IEC	Business Administration	0+2+1	3	ERS
CSI	Business Administration	6+0+1	7	ERS
ESC	Business Administration	9+0+1	10	ERS
ECS	Business Administration	9+4+3	16	ERS
EAS	Communication	9+4+0	13	ESR
ESC	Communication	9+6+2	17	ESR
ECS	Communication	9+2+0	11	ESR
EAC	Communication	9+4+2	15	ESR
ESA	Communication	9+6+1	16	ESR
ECA	Communication	9+2+1	12	ESR
EAS	Communication	9+4+0	13	ESR
ECS	Communication	9+2+0	11	ESR
AER	Communication	3+4+3	10	ESR
EAC	Communication	9+4+2	15	ESR
AEC	Communication	3+4+2	9	ESR
ESA	Communication	9+6+1	16	ESR
SEA	Communication	6+4+1	11	ESR
ESC	Criminal Justice	0+4+1	5	IES
SAE	Education	9+2+1	12	SER
CSI	Education	3+4+2	9	SER
SEA	Education	9+6+1	16	SER
SAC	Education	9+2+2	13	SER
SAE	Education	9+2+1	12	SER
AEC	Education	6+6+2	14	SER
EAS	English	3+4+2	9	ASE
SAE	English	6+4+3	13	ASE
EAS	English	3+4+2	9	ASE

RIASEC Participant Code	Major Used	C-Index computation	C-Index totals	RIASEC Major Code
SAR	English	6+4+1	11	ASE
AES	Fine Arts	9+6+3	18	AES
EAS	Fine Arts	3+2+3	8	AES
ASI	Fine Arts	9+4+1	14	AES
ASE	Fine Arts	9+4+2	15	AES
AIS	Foreign Languages and Cultures	6+2+2	10	ISE
ASC	German	6+6+2	14	ISE
ARE	History	3+0+1	4	ESR
ASR	History	3+6+3	12	ESR
SER	Hospitality Business Management	6+4+3	13	ESR
CES	Human Development	3+6+1	10	SEI
SEA	Human Development	9+6+2	17	SEI
ISC	Human Development	3+4+1	8	SEI
ASE	Humanities	6+4+0	10	SAI
EAS	Humanities	6+6+1	13	SAI
ARE	Interior Design	9+2+2	13	AES
ASE	Interior Design	9+4+2	15	AES
SAI	International Business	6+4+3	13	ESI
ICS	Math	9+4+2	15	IRE
SRA	Movement Studies	9+4+1	14	SIE
SRC	Movement Studies	9+4+2	15	SIE
ERA	Movement Studies	6+4+1	11	SIE
CAS	Natural Resource Sciences	3+2+2	7	IRE
RIA	Natural Sciences	6+4+1	11	IRE
IAR	Neuro Science	9+2+1	12	IRE
SEC	Nursing	9+2+2	13	SIE
IAR	Nursing	3+4+1	8	SIE
SAE	Nursing	9+4+3	16	SIE
EIC	Nursing	6+6+2	14	SIE
RSA	Nursing	0+2+1	3	SIE
SIE	Nursing	9+6+3	18	SIE
AIS	Pharmacy	6+0+1	7	IEC
SER	Political Science	6+4+2	12	ESI
EAI	Political Science	9+4+3	16	ESI
IAR	Pre Med	9+2+0	11	IRS
IES	Pre Med	9+2+3	14	IRS
SAR	Psychology	3+4+1	8	ISE
SAE	Psychology	3+4+3	10	ISE
SEA	Psychology	3+4+1	8	ISE
SEA	Psychology	3+4+1	8	ISE
SEA	Psychology	3+4+1	8	ISE
SEA	Psychology	3+4+1	8	ISE
SAE	Psychology	3+4+3	10	ISE
CIR	Psychology	3+2+1	6	ISE
SEA	Psychology	3+4+1	8	ISE
IES	Psychology	9+4+2	15	ISE

RIASEC Participant Code	Major Used	C-Index computation	C-Index totals	RIASEC Major Code
SIA	Psychology	3+2+1	6	ISE
ECI	Social Sciences	6+2+0	8	SIE
SEC	Social Sciences	9+2+2	13	SIE
RAE	Social Sciences	0+4+3	7	SIE
ASC	Social Sciences	6+2+2	10	SIE
SAI	Sociology	3+2+2	7	IER
ECR	Sociology	3+4+3	10	IER
SCE	Sociology	3+4+1	8	IER
EAS	Sociology	0+2+0	2	IER
SIE	Sociology	3+0+1	4	IER
ASE	Sociology	6+4+1	11	IER
ASI	Soil Science	6+0+1	7	IRS
ISC	Speech and Hearing Science	9+6+2	17	ISR
SCE	Speech and Hearing Science	3+2+1	6	ISR
SCA	Womens Studies	9+4+2	15	SEI
IAR	Zoology	9+2+1	12	IRE

Males

RIASEC Participant Code	Major Used	C-Index computation	C-Index Totals	RIASEC Major Code
RCE	Architecture	6+0+3	9.00	IAE
RIC	Architecture	6+4+2	12.00	IAE
RIA	Architecture	6+4+1	11.00	IAE
RSI	Athletic Training	0+0+3	3.00	SRI
RSC	Athletic Training	0+0+1	1.00	SRI
CRI	Biology	3+2+2	7.00	IAR
RIA	Biology	6+4+1	11.00	IAR
RSI	Biology	6+4+2	12.00	IAR
ACS	Business Administration	3+4+3	10.00	ERS
ECR	Business Administration	9+4+0	13.00	ERS
ERC	Business Administration	9+6+1	16.00	ERS
ECR	Business Administration	9+4+0	13.00	ERS
ERC	Business Administration	9+6+1	16.00	ERS
ERS	Business Administration	9+6+3	18.00	ERS
AER	Business Administration	3+2+0	5.00	ERS
REA	Business Administration	3+2+2	7.00	ERS
RCI	Business Administration	3+4+1	8.00	ERS
RCI	Business Administration	3+4+1	8.00	ERS
ERC	Business Administration	9+6+1	16.00	ERS
RES	Business Administration	3+2+3	8.00	ERS
ECR	Business Administration	9+4+0	13.00	ERS
CEI	Business Administration	6+2+1	9.00	ERS
RCE	Business Administration	3+4+2	9.00	ERS

RIASEC Participant Code	Major Used	C-Index computation	C-Index Totals	RIASEC Major Code
ESA	Business Administration	9+0+2	11.00	ERS
RCI	Business Administration	3+4+1	8.00	ERS
RIC	Chemistry	6+4+2	12.00	IRE
CIR	Civil Engineering	3+4+1	8.00	IRE
RAC	Civil Engineering	6+2+2	10.00	IRE
RSI	Civil Engineering	6+0+0	6.00	IRE
ERA	Communication	9+0+1	10.00	ESR
EAC	Communication	9+4+2	15.00	ESR
ECS	Communication	9+2+0	11.00	ESR
EAR	Communication	9+4+3	16.00	ESR
SAC	Communication	6+4+2	12.00	ESR
IAS	Communication	0+4+0	4.00	ESR
SRA	Communication	6+0+1	7.00	ESR
RES	Communication	3+4+0	7.00	ESR
ARS	Communication	3+0+0	3.00	ESR
ASR	Communication	3+6+3	12.00	ESR
EAS	Comparative Ethnic Studies	0+6+0	6.00	IAR
SCE	Computer Engineering	0+2+2	4.00	RIS
RAI	Computer Science	6+0+1	7.00	ICS
IAC	Computer Science	9+0+1	10.00	ICS
CSE	Criminal Justice	3+4+2	9.00	IES
REC	Criminal Justice	6+6+1	13.00	IES
RAI	Criminal Justice	6+2+1	9.00	IES
RCE	Criminal Justice	6+4+2	12.00	IES
ERC	Criminal Justice	0+2+1	3.00	IES
RCA	Digital Tech and Culture	6+0+1	7.00	IAR
RCE	Digital Tech and Culture	6+0+1	7.00	IAR
REC	Economics	6+4+2	12.00	ISE
REC	Economics	6+4+2	12.00	ISE
RCI	Economics	6+2+0	8.00	ISE
ASC	Education	6+6+2	14.00	ISE
ERA	Electrical Engineering	0+6+1	7.00	IRE
ASE	English	9+6+3	18.00	ASE
ASE	English	9+6+3	18.00	ASE
RIE	Environmental Science	6+0+1	7.00	IER
RIC	Environmental Science	6+0+2	8.00	IER
REC	Finance	3+4+3	10.00	ESC
EAC	Fine Arts	3+2+1	6.00	AES
ARS	Fine Arts	9+2+3	14.00	AES
ARE	Fine Arts	9+2+2	13.00	AES
IRC	Geology	9+6+1	16.00	IRS
RCI	German	6+2+0	8.00	ISE
SIR	History	6+2+3	11.00	ESR

RIASEC Participant Code	Major Used	C-Index computation	C-Index Totals	RIASEC Major Code
RSI	Hospitality Business Management	3+6+2	11.00	ESR
ECR	Hospitality Business Management	9+2+3	14.00	ESR
IAS	Human Development	3+2+1	6.00	SEI
ERC	International Business	9+0+1	10.00	ESI
ERC	Landscape Architecture	3+4+2	9.00	AIR
ESA	Landscape Architecture	3+2+1	6.00	AIR
SEC	Management Information Systems	3+4+2	9.00	ISR
ESC	Management Operations	9+0+1	10.00	ERS
ECR	Marketing	9+2+3	14.00	ESR
IAR	Math	9+2+1	12.00	IRE
RIE	Mechanical Engineering	9+6+3	18.00	RIE
REC	Mechanical Engineering	9+0+2	11.00	RIE
RSI	Movement Studies	0+2+0	2.00	SIE
REA	Natural Resource Sciences	6+2+1	9.00	IRE
AES	Political Science	3+4+1	8.00	ESI
SAR	Political Science	6+4+2	12.00	ESI
REA	Political Science	3+4+2	9.00	ESI
CER	Political Science	6+4+2	12.00	ESI
CER	Political Science	6+4+2	12.00	ESI
CIE	Political Science	6+2+0	8.00	ESI
IEC	Pre med/ Pre Dental	9+2+1	12.00	IRS
CER	Psychology	3+4+1	8.00	ISE
IRA	Psychology	9+0+1	10.00	ISE
SER	Psychology	3+4+1	8.00	ISE
IAR	Psychology	9+4+1	14.00	ISE
IRC	Psychology	9+0+2	11.00	ISE
RIC	Psychology	6+2+2	10.00	ISE
CRE	Psychology	3+0+3	6.00	ISE
ESR	Social Sciences	6+2+1	9.00	SIE
CIR	Social Sciences	3+6+1	10.00	SIE
RES	Social Sciences	0+0+2	2.00	SIE
SER	Sociology	3+6+3	12.00	IER
CRS	Sociology	3+2+0	5.00	IER
IER	Zoology	9+2+1	12.00	IRE