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Modeling The Influences Of Personality Preferences On The Selection Of Instructional Strategies Inintelligent Tutoring Systems

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MODELING THE INFLUENCES OF PERSONALITY PREFERENCES ON THE SELECTION OF INSTRUCTIONAL STRATEGIES IN INTELLIGENT TUTORING SYSTEMS

by

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ABSTRACT

This thesis hypothesizes that a method for selecting instructional strategies (specifically media) based in part on a relationship between learning style preference and personality preference provides more relevant and understandable feedback to students and thereby higher learning effectiveness. This research investigates whether personality preferences are valid predictors of learning style preferences. Since learning style preferences are a key consideration in instructional strategies and instructional strategies are a key consideration in learning effectiveness, this thesis contributes to a greater understanding of the relationship between personality preferences and effective learning in intelligent tutoring systems (ITS).

This research attempts to contribute to the goal of a "truly adaptive ITS" by first examining relationships between personality preferences and learning style preferences; and then by modeling the influences of personality on learning strategies to optimize feedback for each student. This thesis explores the general question "what can personality preferences contribute to learning in intelligent tutoring systems?" So, why is it important to evaluate the relationship between personality preferences and learning strategies in ITS? "While one-on-one human tutoring is still superior to ITS in general, this approach is idiosyncratic and not feasible to deliver to [any large population] in any cost-effective manner." (Loftin, 2004). Given the need for ITS in large, distributed populations (i.e. the United States Army), it is important to explore methods of increasing ITS performance and adaptability.

Findings of this research include that the null hypothesis that "there is no dependency between personality preference variables and learning style preference variables" was partly rejected. Highly significant correlations between the personality preferences, openness and extraversion, were established for both the active-reflective and sensing-intuitive learning style preferences. Discussion of other relationships is provided.

This thesis is dedicated to Shannon, my wife of 25 years. She is my inspiration. Her love and patience allowed me to dedicate the time and effort needed to complete this thesis.

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CHAPTER ONE: GENERAL LITERATURE

Chapter One Summary

In this chapter the motivation for proposed research, the problem domain, scope and application challenges are considered. The basic concepts of intelligent tutoring systems and personality preference theories are reviewed along with general practices, ongoing research programs and trends.

Introduction

"An early promise of intelligent tutoring systems (ITS) was their potential to truly adapt to the individual learner, much as a human tutor engaged in a one-on-one encounter with a student. This goal has proven elusive. ITS still, in most cases, lack the capability for doing dynamic diagnosis (during a learning experience) and, in real time, adapting the current scenario to provide the student with the "optimal" learning experience." (Loftin, 2004).

A significant research and development goal for many universities, government science and technology laboratories and research institutes has been to increase the adaptability of ITS to realize this promise. Researchers have investigated methods to provide tailored feedback to each student based on their needs (knowledge/skill gaps) and they have developed a broader range of human personality attributes (i.e. personality preferences, emotions, social cognition and cultural aspects) into virtual humans and other intelligent tutor interfaces. For many years, educators have embraced the idea of a link between personality preferences and learning style preferences in building human tutoring or instructional strategies. However, these methods have not found their way into ITS.

The research proposed in this thesis attempts to contribute to the goal of a "truly adaptive ITS" by first examining relationships between personality preferences and learning style preferences of the student; and then by modeling the influences of personality on instructional strategies to optimize feedback for each student. This thesis explored the general question "what can personality preferences and learning style preferences contribute to learning in intelligent tutoring systems?"

Motivation for Research: Why is this research important?

Why is it important to evaluate the relationship between personality preferences and learning style preferences in regard to ITS? "While one-on-one human tutoring is still superior to ITS in general, this approach is idiosyncratic and not feasible to deliver to [any large population] in any cost-effective manner." (Loftin, 2004). Given the need for ITS in large, distributed populations (i.e. the United States Army), it is important to explore methods of increasing ITS performance and adaptability.

ITS are expected to provide to the students a content or a skill set they wish to learn, in a way that suits their particular personal, individual learning style preferences and psychological features, delivering the right content to the right user in the right form at the right time. (Rodrigues, 2005). Tutors must "avoid becoming a distraction" (Lane, 2005) by giving too much feedback, asking for too much information, answering the wrong question or answering too slowly.

"From the human-computer interaction point of view a careful examination is necessary of how to adapt the learning environment to the learner's goal and capability" (Oppermann, 1997). This thesis explored methods of adaptability for ITS.

This research hypothesizes that a method for selecting instructional strategies (specifically media) based in part on a relationship between learning style preference and personality preference provides more relevant and understandable feedback to students and thereby higher learning effectiveness. This research explored whether personality preferences were valid predictors of learning style preferences. Since learning style preferences are a key consideration in instructional strategies and instructional strategies are a key consideration in learning effectiveness, the goal of this thesis was to demonstrate the relationship between personality preferences and effective learning in ITS. If successful, this method could be applied across domains and various student populations as an adaptive pedagogical model for instructional strategy selection.

Problem Domain and Scope of Research

This research focused on the pedagogical aspects of intelligent tutoring systems and specifically methods for selecting media that is compatible with an individual student's preferred learning style and his perceived knowledge/skill gaps. This thesis developed a predictive model that uses student learning style preferences to aid in the selection of appropriate instructional strategies (specifically media). Ideally, the proposed research would link media selection to student performance history, identified knowledge and skill gaps. Given the complexity of that task, resources and the need for focus, the researcher narrowed his investigation to the examination of personality preferences as predictors of learning style preferences and media selection tools.

Application Challenges

The amount and type of feedback provided to students by ITS is a significant issue. Too little feedback can lead to frustration and floundering (Anderson, 1993) and too much feedback can interfere with learning (Kashihara, 1994). The selection method for feedback and other instructional strategies are limited in ITS. Ideally, the student model should influence the selection of instructional strategies so that the strategies selected are most effective for teaching that particular student. One of the key differences between students is their personality preferences (i.e. how they take in information and make decisions with that information). (Myers, 1998) Making a link between appropriate instructional strategies and personality preferences would go a long way in making ITS truly adaptable to each student's needs.

General Practices: Model Development Processes

This section examines general concepts and trends in two areas related to the scope of the research proposed in this thesis: intelligent tutoring systems modeling and personality preference modeling.

Dimensions of Intelligent Tutoring System Modeling

"Broadly defined, an intelligent tutoring system is educational software containing an artificial intelligence component. The software tracks students' work, tailoring feedback and hints along the way. By collecting information on a particular student's performance, the software can make inferences about strengths and weaknesses, and can suggest additional work." (Hafner, 2004)

An intelligent tutoring "system must be capable of dynamically adapting and monitoring each student." (Rodrigues, 2005) The mere presentation of information does not qualify as instruction. (Liegle, 2000) ITS are expected to perform the following tasks (Rodrigues, 2005):

- Provide to the students a content or a skill set they wish to learn, in a way that suits their particular personal, individual learning style preferences and psychological features, delivering the right content to the right user in the right form at the right time;
- Advise the student, on how he should learn the content or skills and help him to work on a suitable study schedule;
- Co-work with the student in monitoring the learning schedule;
- The monitoring of students learning schedule integrated in the process of collaborative knowledge, namely because students must be aware from other's activities and the collaboration with other persons (students, instructors) must be regulated;
- Intelligent interactive analysis performed on what the students are doing and providing real time diagnostic help

"A tutoring system should try to improve students' metacognitive skills, by, for example, guiding a student who avoids using help to seek help at the right moment." (Roll, 2005)

General Concepts/Definitions for Intelligent Tutoring Systems

There are many variants of ITS block diagrams, but in general, ITS contain four major components as identified by Woolf (1992): the student model, the pedagogical module, the domain knowledge module, and the communication module. Beck (1996) identified a fifth component, the expert model, which Woolf included as part of the domain knowledge module. These components, their functions and interactions are described below:

- **Student Model or Performance History Model**: The student model is a record of the student's knowledge state (Corbett, 1997). It stores information specific to each individual learner including a history of performance and other pertinent data. This could include personality preference information or other state information. The student model also records observable actions and may (through some fuzzy logic) infer non-observable states (i.e confusion, boredom or other emotions). "Since the purpose of the student model is to provide data for the pedagogical module of the system, all of the information gathered should be able to be used by the tutor [pedagogical module]." (Beck, 1996)
- **Pedagogical Module or Instructional Planner**: This component provides a model of the instruction process and contains logic for making decisions about when to review information, when to present new topics or concepts. The sequencing of topics is controlled by the pedagogical module. Once the topic has been selected, a problem must be generated for the student to solve and then feedback is provided on the student's performance. As noted above, the student model is used as input to this component, so the pedagogical decisions reflect the differing needs of each student.

- **Domain Knowledge**: This component contains information the tutor uses to instruct the student. It is critical that the domain be accessible by other parts of the ITS. "One related research issue is how to represent knowledge so that it easily scales up to larger domains. Another open question is how to represent domain knowledge other than facts and procedures, such as concepts and mental models." (Beck, 1996) This component contains items like generic instructional strategies, databases of scenarios and diagnostics.
- **Communications or Interface Module**: This component controls interactions with the learner, including the dialogue and how the material should be presented to the student in the most effective way. This selection of presentation format is driven by the selection of instructional strategies in the pedagogical module. The communications module may also include some type of natural language understanding function to support verbal interaction with the student.

- **Expert Model**: This component is also know as the Cognitive Model of Ideal Student Behaviors as shown in Figure 2 above. The expert model is similar to the domain knowledge in that it is a model of how someone skilled in a particular domain represents the knowledge. Generally, it takes the form of a runtime expert model (i.e. one that is capable of solving problems in the domain). (Clancey, 1981) "By using an expert model, the tutor can compare the learner's solution to the expert's solution, pinpointing the places where the learner had difficulties." (Beck, 1996)

General Practices in Intelligent Tutoring Systems

Below are several approaches to the development of intelligent tutoring systems. Each of these approaches supports a particular learning style preference (i.e. deductive, inductive or exploratory). In the literature search conducted, it was rare to find a tutor that encompassed more than two of these approaches. Given the variance in human personality, an adaptable tutor that encompassed all of these approaches and others would be desirable.

- **Human emulation of a tutor**: This approach uses natural language processing to interact with the student and may use some type of virtual human (i.e. embodied conversational agent). This approach is similar to dealing with a human, but is very difficult to model given the requirement to provide real-time reactions (verbal and non-verbal) to student inquiries. Success with this type of tutor has been limited and the cost for this type of approach has been higher than others.
- **Bug Detection**: "There are classically two components in a student model: an overlay of the domain expert knowledge and a bug catalog, which is a set of misconceptions or incorrect rules." (Corbett, 1997) In a bug detection scheme, the tutor corrects errors by explaining what the error is (i.e. the student is using the rules properly, but the problem is that it is the wrong rule is being applied). A drawback to this approach is that too frequent intervention by the tutor can detract from the learning experience.
- **Exploratory systems** (discovery worlds, micro worlds): Exploratory systems are environments that "place less emphasis on supporting learning through explicit instruction and more on providing the learner with the opportunity to explore the instructional domain

freely, acquiring knowledge of relevant concepts and skills in the process" (Shute, 1990). A drawback to this approach is that learning may be time intensive and very inefficient. Given sufficient time, this approach may be very appealing for some learners. Smithtown, which provides a guided discovery of economics, is an example of an exploratory system.

- **Model Tracing**: A cognitive model of the task is developed through a task analysis. Student progress is assessed by ``tracing" the student's task actions (i.e., matching user and application events against the task model). The student is permitted to consult task model as needed. This approach seems to be the most prevalent and tied closely to cognitive models like ACT-R (Anderson, 1993) and SOAR (Lehman, 2006).
- **Constructivism**: "Constructivism is a philosophy of learning founded on the premise that, by reflecting on our experiences, we construct our own understanding of the world we live in. Each of us generates our own "rules" and "mental models," which we use to make sense of our experiences. Learning, therefore, is simply the process of adjusting our mental models to accommodate new experiences." (Funderstanding.com, 2006). In this approach, the ITS provide opportunities for the student to participate in the instructional process. There are no standardized curricula, tests or grades. Instead, constructivism promotes the use of customized curricula based on the student's prior knowledge and emphasizes hands-on problem solving and reflection.

Research in Intelligent Tutoring Systems

There are several issues that have been drivers for recent research in ITS. These include: high development costs, lack of interoperability, restrictive delivery platform requirements, difficulty of sharing materials and benchmarking and high maintenance costs (Rodrigues, 2005).

Below are several recommendations for future research thrusts in ITS:

- **Ontology**: Ontology is defined as “a controlled vocabulary that describes objects and the relations between them in a formal way, and has a grammar for using the vocabulary terms to express something meaningful within a specified domain of interest. The vocabulary is used to make queries and assertions. Ontological commitments are agreements to use the vocabulary in a consistent way for knowledge sharing.” (Browne, 2001). “Structured ontologies or upper models that define and organize pedagogically relevant attributes of knowledge for classes of domains, enabling the writing and sharing of instructional strategies in terms of these attributes.” (Rodrigues, 2005) “The systematic development of a formal ontology must be pursued, and the results of this effort widely disseminated. Such an effort will serve to focus attention on this critical “missing piece” and generate the necessary discussions within the Intelligent Tutoring System research community to achieve a reasonable degree of consensus.” (Loftin, 2004)
- **Architectures**: “A study is required to map current Intelligent Tutoring System capabilities to a selected training/education domain. This mapping will then identify the small number of architectures that must be supported during application development.” (Loftin, 2004)

"Architectures and protocols involving collaborating processes or shared knowledge bases which address issues of modularity and reusability." (Rodrigues, 2005)

- **ITS Adaptability**: "Basic research is needed to address one of the central "promises" of Intelligent Tutoring Systems—the maturation of systems capable of user adaptability. This is a well-traveled research element that has led to the development of different approaches, none of which has achieved success outside of narrow domain applications." (Loftin, 2004) *ITS adaptability is the focus of the research proposed in this thesis*.
- **Motivation**: Research "should be initiated to (1) investigate means to measure learner motivation within an Intelligent Tutoring System and (2) develop mechanisms to enhance learner motivation through scenario creation and feedback from the Intelligent Tutoring System." (Loftin, 2004)
- **Virtual Humans**: "Research on the value of virtual humans as an adjunct to or element of an Intelligent Tutoring Systems should be conducted. The potential value of virtual humans may be high, but it remains to be demonstrated." (Loftin, 2004) Perhaps a comparison of interface and feedback mechanisms that include virtual humans should be examined.
- **Team Training**: Few examples of Intelligent Tutoring Systems for team training have been attempted and the results have not provided convincing evidence that we understand how to develop such systems successfully. (Loftin, 2004)

Rodrigues recommends additional efforts in several areas including: reusable components, standardization of existing software architectures, standardization for interoperability of ITS, personalization techniques, case-based reasoning and adaptive hypermedia.

Dimensions of Personality Modeling

There are many facets to personality modeling including, but not limited to emotions, motivation, trust, learning, social factors and decision-making. In this section, we concentrated on only two concepts in personality modeling related to the research in this thesis: learning style preferences and personality preferences.

General Concepts/Definitions for Learning Preference Modeling

In order to understand learning style preferences, we must first define learning. In reviewing several definitions, this description of learning provides a clearest and comprehensive definition of learning: "Learning is the process of acquiring knowledge, skills, attitudes, or values, through study, experience, or teaching, that causes a change of behavior that is persistent, measurable, and specified or allows an individual to formulate a new mental construct or revise a prior mental construct (conceptual knowledge such as attitudes or values). It is a process that depends on experience and leads to long-term changes in behavior potential. Behavior potential describes the possible behavior of an individual (not actual behavior) in a given situation in order to achieve a goal. But potential is not enough; if individual learning is not periodically reinforced, it becomes shallower and shallower, and eventually will be lost in that individual." (Wikipedia, 2006a)

"Learning styles are different ways that a person can learn. It's commonly believed that most people favor some particular method of interacting with, taking in, and processing stimuli or information." (Wikipedia, 2006b) However, this may not mean that they use this style exclusively. Keefe (1979) defines "learning styles" as characteristic cognitive, affective and psychological behaviors that serve as relatively stable indicators of how learners perceive, interact with and respond to the learning environment.

“Preference (or "taste") is a concept, used in the social sciences, particularly economics. It assumes a real or imagined "choice" between alternatives and the possibility of rank ordering of these alternatives, based on happiness, satisfaction, gratification, enjoyment, utility they provide. More generally, it can be seen as a source of motivation. In cognitive sciences, individual preferences enable choice of objectives/goals.” (Wikipedia, 2006c)

For the purpose of this research, the term “learning style preference” combines the notions of preference and learning style to indicate a particular learning style preferred by a student.

There are currently over seventy learning style preference instruments and theories of learning and several other instruments which have conducted correlation studies between their factors and learning style preferences. A sample of these instruments includes, but is limited to:

- Entwistle’s Approaches and Study Skills Inventory for Students (ASSIST)
- Fleming’s VARK Learning Styles Questionnaire
- Gardner’s Theory of Multiple Intelligences
- Honey and Mumford’s Learning Styles Questionnaire (LSQ)
- Jackson’s Learning Styles Profiler (LSP)
- Kolb’s Learning Style Inventory (LSI)
- Riding’s Cognitive Styles Analysis (CSA)
- Sternberg’s Thinking Styles Inventory (TSI)
- Vermunt’s Inventory of Learning Styles (ILS)

- Felder and Silverman's Index of Learning Styles (ILS)

For example, Kolb (1984) has developed a learning cycle model called the Experiential Learning Model (ELM) which identifies four ways in which people learn:

- through concrete experience
- through observation and reflection
- through abstract conceptualization
- through active experimentation

Kolb's ELM has become a model for adult learning. The use of the ELM cycle (all four styles) insures that all learning types are engaged in the learning process.

General Practices in Learning Preference Modeling

As noted previously, *several learning preference instruments are being examined as potential candidates to validate student learning style preferences against any experimental results generated under this thesis.* The selection of a single instrument is difficult when over seventy are available. This task may be easier given the validity of several widely used instruments has been questioned. In 2004, a report titled "Learning styles and pedagogy in post-16 learning – a systematic and critical review" was published by the Learning and Skills Research Centre in the United Kingdom.

This study selected 13 of the most influential models for close examination. To ensure consistency they applied the same criteria to each: examining theoretical origins, definition of terms, the instrument itself, the claims made by the author(s), external studies of these claims and independent empirical evidence of impact on teaching and learning (Coffield, 2004).

The Coffield report concluded for many of the learning style inventories that "Moreover, self-report inventories 'are not sampling learning behaviour but learners' impressions' (Mitchell 1994) of how they learn, impressions which may be inaccurate, self-deluding or influenced by what the respondent thinks the psychologist wants to hear. As Price and Richardson (2003) argue: 'the validity of these learning style inventories is based on the assumption that learners can accurately and consistently reflect: how they process external stimuli and what their internal cognitive processes are."

Research in Learning Preference Modeling

At the MIT Media Laboratory, research in affective computing is examining the impact of emotions on learner preferences. "Recent neurological evidence indicates that emotions are not a luxury; they are essential for "reason" to function normally, even in rational decision-making. Furthermore, emotional expression is a natural and significant part of human interaction. Whether it is used to indicate like/dislike or interest/disinterest, emotion plays a key role in multimedia information retrieval, user preference modeling, and human-computer interaction. Affective computing is a new area of research focusing on computing that relates to, arises from, or deliberately influences emotions. The focus of the present project is on giving computers the ability to recognize affect. Current applications include better learning systems (computer recognizes interest, frustration, or pleasure of pupil), and smarter "things" such as a steering wheel/seatbelt that sense when a driver is angry or incapacitated." (Picard, 2006)

Ahn (2006) recently demonstrated that affective biases from affective anticipatory rewards could be applied for improving the speed of learning and regulating the trade-off between exploration and exploitation in learning more efficiently. Her model of affective anticipatory reward is based two dimensions: valence (good or bad) and uncertainty (hopeful or risky). For example: recognizing the student's smugness or boredom might cause the tutor to raise the "uncertainty of reward" to influence (affect) the student's attitude and level of engagement.

General Concepts/Definitions for Personality Preference Modeling

In order to understand personality preferences, we must first define personality. This definition was selected as clear and comprehensive: "personality is defined as individual difference constructs (traits) that manifest themselves through recurring regularities or trends in a person's behavior that are dependent primarily on conscious or unconscious volition as opposed to ability." (Hunt, 2003)

Preferences are the natural choice to use one mode of operation over use the other mode of operation. So, we are said to "prefer" one function over the other. Personality preference is the essence of Carl Jung's theory of psychological types. Jung stated that "much seemingly random variation in behavior is actually quite orderly and consistent, being due to basic differences in the way individuals prefer to use their perception and their judgment." (Myers, 1998)

The basis for many of the personality preference theories are Carl Jung's two dimensions of personality: perception (gathering data; taking in information; observing the world around you) and judging (evaluating data; making decisions on information; critiquing your observations) (Myers, 1998). Jung's theories are based on the observation of his clients. Of the three most prevalent personality preference models, Myers-Briggs Type Indicator (MBTI) and Keirsey Temperament Sorter (KTS) have their basis in Jung's theories. KTS and the Five Factor

Model (FFM) Model of Personality are evolutions of MBTI. MBTI and KTS are theory-based, while FFM is empirically-based.

General Practices in Personality Preference Modeling

The advent of the FFM taxonomy in the 1980s helped produce order in a previously scattered and disorganized field. “Research had found that "personality" (i.e., any of a large number of hypothesized personality traits) was not predictive of important criteria. However, using the five-factor model as a taxonomy to group the vast numbers of unlike personality traits, a meta-analysis of previous research was shown to have many significant correlations between the personality traits of the five-factor model and job performance in many jobs. Their strongest finding was that the psychometric Conscientiousness was predictive of performance in all the job families studied.” (Wikipedia, 2006d)

Research in Personality Preference Modeling

A search of the research database of the Center for Applications of Psychological Type (CAPT), MBTI’s primary research center, yielded 249 publications related to “learning styles” and “personality type”. About a dozen publications relate to learning strategies, styles and MBTI. None of these publications was related to “intelligent tutoring” or “affective computing”.

Most of the research in recent years on learning style preferences and personality type has centered on the correlation of the sixteen MBTI types and data on educational performance and behaviors that contribute to educational performance (Myers, 1998). The results show that each MBTI dichotomy is related to the certain characteristics of learners (Myers, 1998). For example, extraverts may be characterized as concrete experiential learners or active experimental learners. Introverts might be characterized as abstract sequential learners.

This research does not provide a measure of probability for these factors (i.e. if a student is an ESTJ (extraverted-sensing-thinker-judger) and some of the characteristics of E's conflict with S's, T's and J's, which factor has the higher probability or tendency to resulting in an attitude (unobserved characteristic) or a behavior (observed characteristic)). Conflicting characteristics can even appear within the same factor.

Current research for the FFM is generally concentrated in three areas (Wikipedia, 2006d):

- Are the five factors the right ones? Why not four or seven or three?
- Which factors predict what? "Job outcomes for leaders and salespeople have already been measured, and research is currently being done in expanding the list of careers. There are also a variety of life outcomes which preliminary research indicates are affected by personality, such as smoking (predicted by high scores in Neuroticism and low scores in Agreeableness and Conscientiousness) and interest in different kinds of music (largely mediated by Openness)."
- To make a theory-based model of personality. The FFM personality traits are empirical observations, not theory.

General Research Gap and Research Questions

There is a plethora of studies that show correlation between personality preferences and learning style preferences. However, based on Coffield's (2004) analysis, the construct validity and predictive validity of many learning style preference instruments and the MBTI is questionable. In conducting the literature search for this thesis, no correlation study showing the relationship of an empirical personality preference model (i.e. the Five Factor Model) as a predictor of validated learning style preferences was found. No adaptive ITS was found that utilized personality as predictor to select learning strategies.

Research Gap: Correlation of personality preferences and research preferences

The prevalence of the instrument is not a measure of validity. The first step is to find a validated learning preference model. One that has been demonstrated to contain factors that when present, positively impact learning outcomes. Predicting correct learning strategies based on a correlation with a student's personality preferences will improve learning. Predicting incorrect or invalid strategies will not.

Research Questions

- Why not just give the student a learning style preferences survey instead of trying to predict learning style preferences from personality preferences? If the personality preferences are good predictors of learning style preferences, they may be good predictors of other behaviors (i.e. motivation, trust, emotions and other attitudes) and it would be more efficient to use one survey that could predict all those factors.
- How do personality preferences relate to learning style preferences? Is there a strong correlation?
- Are personality preferences good predictors of learning style preferences? If they are, then they could aid in the optimal selection of instructional strategies/tactics within intelligent tutoring systems. The predictive nature of personality preferences based on the input of five numbers (factors) would reduce the interface load and interventions between the student and

the tutor that would otherwise be required to assess whether the strategies presented to the student were effective.

- Which models and methods would work best to demonstrate a correlation between personality preferences and learning style preferences?

CHAPTER TWO: APPROACHES, TECHNIQUES, MODELS AND MEASURES

What approaches exist that might address the operational or technical need for adaptive ITS and why they are inadequate?

Chapter Two Summary

This chapter examines current and developing models of intelligent tutoring systems and personality preferences with eye toward how they might be integrated, extended or otherwise modified to support the proposed research goals and tasks. Six intelligent tutoring systems and their pedagogical models were evaluated: the LISP tutor, the blackboard instructional planning system, the Smithtown economics tutor, COGNET, SHERLOCK and ABITS. Two prevalent learning preference theories were reviewed: Gardner's "Multiple Intelligences" and Fleming's VARK Learning Styles. Two prevalent personality preference models were reviewed: the Myers-Briggs Type Indicator® (MBTI) and the Five Factor Model (FFM) of Personality. Specific advantages and disadvantages of each ITS and preference model are discussed. A specific research gap is identified and a concept to address that gap is proposed.

Models, Techniques, Approaches and Measures used by other Authors and Researchers

Intelligent Tutoring System Models

A review of ITS models and approaches is provided in this section.

LISP tutor

The LISP tutor (Anderson and Reiser 1985) is an Intelligent Tutoring System developed to teach the basic principles of programming in LISP. The expert model in the LISP tutor was created as a series of correct production rules for creating LISP programs and a learner model was built as a subset of these correct production rules along with common incorrect production rules (Holt et al 1991).

LISP tutor is based on the principle of "learning by doing" where the learner discovers the productions while working through problems. The tutor acts as a problem solving guide but never states the productions to be learned. The LISP Tutor is an application of Anderson's ACT theory (Anderson 1983).

ACT theory is one of the earliest attempts to establish a complete theory of human cognition. It combines declarative knowledge in the form of semantic nets with procedural knowledge in the form of production rules. In ACT learning is accomplished by forming new procedures through the combination of existing production rules. The main principles of the ACT theory are:

- Cognitive functions can be represented as a set of production rules. The use of a production rule depends on the state of the system and the current goals.
- Knowledge is learned declaratively through instructions. The learner must carry out the process of knowledge compilation if the productions are to be properly understood and integrated into their existing knowledge and later recalled and used.

Anderson represented the knowledge in LISP tutor as approximately 325 production rules. The system also had about 425 buggy production rules which represented the misconceptions of novice programmers.

The LISP tutor used model tracing to provide the learner with detailed feedback. The learner would be given a problem and the tutor would monitor the learners input character by character. The tutor generates all the possible next characters using both correct and buggy production rules.

- If the character is predicted by the correct rule the learner is allowed to continue.
- If the character is predicted by a buggy production rule remedial instructions is given.
- If the character is not predicted the tutor says that it cannot understand and asks the learner to try again. After several tries the tutor explains the next step.

This method has the advantages of early diagnosis of learner misconceptions and of giving immediate feedback to the learner. The learner never strays far from a correct solution. However, this can be viewed as unnecessarily restrictive and counter productive as the student is never allowed to explore incorrect behavior.

Blackboard instructional planning system

Blackboard instructional systems are ITS focused on "how to teach" (i.e. instructional activities like when to test, demonstrate, review or conduct "dynamic planning"). Blackboard instructional systems are composed of:

- a hierarchically structured global database
- independent knowledge sources – production rules that change the global database
- an agenda scheduler
- knowledge source activation record – agenda of prioritized actions to be executed

Blackboard systems operate as follows:

- tutor compares student's choice to domain expert's model (represented as a semantic network) and updates the student model

- when the difference between the student model and expected performance indicates failure of instruction, diagnosis is begun in order to identify the prerequisite skill most likely to have been misunderstood
- upon diagnosis (i.e. a student has failed to answer a multiple choice question correctly), the appropriate missing prerequisite is spliced into the lesson plan

The control blackboard in the blackboard instructional planner:

- refines and assesses objectives: what needs to be taught in terms of instructional objectives
- relates activities to objectives: proposes, prioritizes, filters, sequences, and critiques activities that support objectives
- relates procedures to activities: proposes, selects, sequences, and critiques actions that support activities
- partitions lessons

Smithtown economics tutor

Smithtown is an ITS designed as a guided discovery world. Smithtown's goals are to teach students the scientific inquiry process (how to solve problems). It imparts knowledge and prompts actions consistent with good inquiry skills (thinking and planning):

- tendency to test generalizability of hypotheses
- use of adequate data collection in testing hypotheses
- tendency to test systematically (change one variable at a time)
- tendency to thoroughly investigate cause-effect relationships

- tendency to volunteer predictions with respect to outcomes

Its secondary goal is to impart specific content knowledge in microeconomics, specifically the laws of supply and demand. Smithtown diagnoses student performance by comparing student performance with buggy critics (suboptimal behavior) and good critics (expert solutions) – as in model tracing. This critic information is fed to the Smithtown coach who then guides the student's learning experience (Shute, 1990).

Sherlock

Sherlock, was developed in the early 1990s to train Air Force personnel on jet aircraft troubleshooting procedures. Learners taught using Sherlock performed significantly better than the control group and, after 20 hours of instruction, performed as well as technicians with four years of on-the-job experience. (Ong, 2006)

A Cognitive Modeling Framework (COGNET)

The main components of the COGNET cognitive modeling language are: a problem representation blackboard containing declarative knowledge about the situation, procedural knowledge represented as tasks, and mechanisms for sensing the external environment (perceptual demons) and then acting on it (actions). (Ryder, 2000)

Agent-Based Intelligent Tutoring System (ABITS)

ABITS is organized as a Multi Agent System (MAS) composed by pools of three different types of agents (evaluation, pedagogical and affective agents). Each agent is able to solve in autonomous way a specific task and they work together in order to improve web-based tutoring learning effectiveness by adapting instructional materials to user skills and preferences (Capuano, 2000).

The ABITS concept is compatible with the research goal proposed in this thesis in that it considers the learner's preferences. However this approach does not include consideration for personality preferences as predictors for learning style preferences. The learning style preferences selected by the course management system are based on evaluations of the pedagogical effectiveness of learning object typologies. For example, if the knowledge of a particular concept has been primarily simulation-based, ABITS infers that the student is receptive to simulations and the system increases the "format" preference that refers to simulations. This could be very cumbersome since it is unclear how often this type of assessment must be made or how much information is needed to make clear distinction between each of the choices of format. Formats can include text, images, slides, hypertext, video, simulations or even virtual reality. In ABITS, the approach (inductive, deductive or explorative) can vary along with interactivity level, semantic density and level of difficulty.

Learning Preference Models

This section reviews multiple learning preference theories including Gardner's "Multiple Intelligences" and Fleming's "VARK Learning Styles".

Theory of Multiple Intelligences

The theory of multiple intelligences was developed in 1983 by Dr. Howard Gardner, professor of education at Harvard University who maintained that we solve problems in seven distinct styles and that each style is an "intelligence". He theorizes that most people learn by blending several of these styles (Gardner, 1999). Learning style preferences are shown in italics for each intelligence. The seven intelligences are:

- **Verbal/Linguistic Intelligence**: This intelligence, which is related to words and language. It is the ability to think in words and to use language to express and appreciate complex meanings. This includes both written and spoken language. It is the most widely shared human competence and is evident in poets, novelists, journalists, and effective public speakers. Characteristics of this intelligence are:
  - likes to: read, write and tell stories
  - is good at: memorizing names, places, dates and trivia
  - ***learns best by: saying, hearing and seeing words***
- **Logical/Mathematical Intelligence**: Often called "scientific thinking," this intelligence deals with inductive and deductive thinking/reasoning, numbers and the recognition of abstract patterns. It includes the ability to calculate, quantify, consider propositions and hypotheses, and carry out complex mathematical operations. Logical intelligence is usually well developed in mathematicians, scientists, and detectives. Characteristics of this intelligence are:
  - likes to: do experiments, figure things out, work with numbers, ask questions and explore patterns and relationships
  - is good at: math, reasoning, logic and problem solving
  - ***learns best by: categorizing, classifying and working with abstract patterns/relationships***

- **Visual/Spatial Intelligence**: This intelligence, which relies on the sense of sight and being able to visualize an object, includes the ability to create internal mental images/pictures. It is the ability to think in three dimensions. Sailors, pilots, sculptors, painters, and architects all exhibit spatial intelligence. Characteristics of this intelligence are:
    - likes to: draw, build, design and create things, daydream, look at pictures/slides, watch movies and play with machines
    - is good at: imagining things, sensing changes, mazes/puzzles and reading maps, charts
    - ***learns best by: visualizing, dreaming, using the mind's eye and working with colors/pictures***
- **Body/Kinesthetic Intelligence**: This intelligence is related to physical movement and the knowing/wisdom of the body. It is the capacity to manipulate objects and use a variety of physical skills. Athletes, dancers, surgeons, and craftspeople exhibit well-developed bodily-kinesthetic intelligence. Characteristics of this intelligence include:
    - likes to: move around, touch and talk and use body language
    - is good at: physical activities (sports/dance/acting) and crafts
    - ***learns best by: touching, moving, interacting with space and processing knowledge through bodily sensations.***
- **Musical/Rhythmic Intelligence**: This intelligence is based on the recognition of tonal patterns, sounds, and sensitivity to rhythm and beats. It is the capacity to discern pitch,

rhythm, timbre, and tone. This intelligence is demonstrated by composers, conductors, musicians, vocalists, and sensitive listeners. Characteristics of this intelligence include:

  - likes to: sing, hum tunes, listen to music, play an instrument and respond to music
  - is good at: picking up sounds, remembering melodies, noticing pitches/rhythms and keeping time
  - ***learns best by: rhythm, melody and music***

- **Interpersonal Intelligence**: This intelligence operates primarily through person-to person relationships and communication. It is the ability to understand and interact effectively with others. Teachers, social workers, actors, and politicians all exhibit interpersonal intelligence. Characteristics of this intelligence include:
  - likes to: have lots of friends, talk to people and join groups
  - is good at: understanding people, leading others, organizing, communicating, manipulating and mediating conflicts
  - ***learns best by: sharing, comparing, relating, co-operating and interviewing***
- **Intrapersonal Intelligence**: This intelligence relates to inner states of being, self-reflection, metacognition (i.e., thinking about thinking) and awareness of spatial realities. It is the capacity to understand oneself and one's thoughts and feelings and to use such knowledge in planning and directing one's life. It involves not only an appreciation of the self, but also of the human condition. It is evident in psychologists, spiritual leaders, and philosophers. Characteristics of this intelligence include:
  - likes to: work alone and pursue own interests

- is good at: understanding self, focusing inward on feelings/dreams, following instincts, pursuing interests/goals and being original
- ***learns best by: working alone, on individualized projects, with self-paced instruction and having their own space***

VARK Learning Styles

VARK (Fleming, 2001) evolved around the learner's preference for taking in and giving information in a learning context. It has four modalities: visual, aural, reading/writing and kinesthetic. The results of the VARK questionnaire include a description of an individual's stronger preferences and recommended study strategies.

Visual Learning Style (V): This style includes the need for information in charts, graphs, flow charts, and all the symbolic arrows, circles, hierarchies and other devices that teachers use to represent what could have been presented in words. This mode does not include pictures, movies, videos, virtual simulations or animated websites because they are multimodal (visual, aural, read/write and kinesthetic. (Fleming, 2001)

Aural Learning Style (A): This perceptual mode describes a preference for information that is "heard and spoken". Learners with style report that they learn best from lectures, group discussion, tutorials, student seminars and talking with other students.

Read/Write Learning Style (R): This modal preference is for information displayed as text and printed words. Many teachers in Western cultures have a strong preference for this modality.

Kinesthetic Learning Style (K): By definition, this modality refers to the "perceptual preference related to the use of experience and practice (simulated or real)." Although such an experience may include other modalities, the key is that the student is connected to reality, "either through experience, example, practice or simulation". (Fleming & Mills, 1992) In this style, students use many senses (sight, tough, taste, hearing, speaking and smell) to experience something new.

The Index of Learning Styles (ILS)

The Index of Learning Styles © (ILS) is an instrument designed to assess preferences on the four dimensions of the Felder-Silverman learning style model (see Appendix B). The Web-based version of the ILS is taken hundreds of thousand of times per year and has been used in a number of published studies, some of which include data reflecting on the reliability and validity of the instrument. The model's dimensional pairs are a continuum not a dichotomy. A dimension like "sensing" could be classified as mild, moderate or strong and resulting profiles suggest behavioral tendencies rather than being infallible predictors of behavior (Felder and Silverman, 2005). The dimensions of the ILS are:

- **sensing** (concrete thinker, practical, oriented toward facts and procedures) or **intuitive** (abstract thinker, innovative, oriented toward theories and underlying meanings);
- **visual** (prefer visual representations of presented material, such as pictures, diagrams and flow charts) or **verbal** (prefer written or spoken explanations)
- **active** (learn by trying things out, enjoy working in groups) or **reflective** (learn by thinking things through, prefer working alone or with a single familiar partner)

- **sequential** (linear thinking process, learn in small incremental steps) or **global** (holistic thinking process, learn in large leaps)

Personality Preference Models

There are numerous personality preference models available for use in this research including the Keirsey Temperament Sorter, Strength Deployment Inventory, Myers-Briggs Type Indicator® (MBTI), Cattell's 16 Personality Factor Model, the Murphy-Meisgeier Type Indicator for Children and the Five Factor Model (FFM). For the purposes of this thesis, we examined two of the most prevalent preference models: MBTI and the FFM. This choice was made based on availability, ease of use, the need to limit scope and examine models that represent the variability of preferences in adults vice children or infants.

Myers-Briggs Type Indicator® (MBTI)

Currently MBTI is the most widely utilized personality preference instrument in the world is a tool designed to implement the theories of C. G. Jung, a Swiss psychiatrist, who developed a comprehensive theory to explaining human personality. Jung hypothesized that "Much seemingly chance variation in human behavior is not due to chance; it is in fact the logical result of a few basic, observable preferences." (Kroeger, 2001)

The MBTI instrument was developed by Katherine Briggs and Isabel Briggs Myers to make C. G. Jung's theory of personality types practical and useful in people's lives. MBTI reflects an individual's preferences, but does not measure abilities, likelihood of success, intelligence, skills, maturity or mental health. This tool aids in achieving an understanding of the differences of others. Specifically, MBTI assesses preferences based on Carl Jung's two functions of personality: perception (gathering data; taking in information; observing the world around you) and judging (evaluating data; making decisions on information; critiquing your observations) (Myers, 1998).

There are sixteen (16) personality types based on four (4) dichotomies (two functions and two attitudes) as follows:

- **Perceiving function** (sensing or intuiting): Sensing (S) people seek the fullest possible experience of what is immediate and real while Intuitive (N) people seek the furthest reaches of the possible and imaginative (Myers, 1998).
- **Judging function** (thinking or feeling): Thinking (T) people seek rational order in accord with the non-personal logic of cause and effect while Feeling (F) seeks rational order in accord with the creation and maintenance of harmony among important subjective values (Myers, 1998). By the way, it is not true that thinkers don't feel and feelers don't think!
- **Energy Source attitude** (introversion or extraversion): For Extraverts (E) energy and attention flow out or are drawn out to objects and people in the environment while Introverts (I) draw energy from the environment toward inner experience and reflection (Myers, 1998).
- **Lifestyle Orientation attitude** (judging or perceiving): The Judging (J) attitude is concerned with making decisions, seeking closure, planning and organizing while the Perceiving attitude is attuned to taking in information (Myers, 1998).

None of the four dichotomies stand alone, but are part of an interactive system where the lifestyle orientation (judging or perceiving) drives which of the four functions (sensing, intuition, thinking and feeling) are dominant. The sixteen (16) types, shown in Table 1, represent preferences and personal interactions. People of the same type tend to take in information and make decisions in a similar way. It doesn't mean they do everything the same or that they only do things one way. It means they have preferences for how they do things and in the absence of stress follow these preferences.

Table 1: The 16 personality types in MBTI (Myers, 1998)

ISTJ	ISFJ	INFJ	INTJ
ISTP	ISFP	INFP	INTP
ESTP	ESFP	ENFP	ENTP
ESTJ	ESFJ	ENFJ	ENTJ

Five-Factor Model (FFM)

The Five-Factor Model (FFM) is a much newer model than MBTI that has taken hold in the scientific community. The Big Five Personality Test (John, 2003) is a representative instrument that measures the five dimensions of the FFM. The FFM is not a radical departure from the MBTI. It evolved from it. However, FFM is sufficiently different from MBTI to require a significant shift in thinking. Per Howard (2004) the characteristics of FFM include:

- five dimensions of personality (vice four in MBTI);
- a normal distribution of scores on these dimensions (vice a bi-modal distribution [dichotomy] in MBTI);
- an emphasis on individual personality traits (vice the type concept in MBTI);

- preferences indicated by strength of score, and
- a model based on experience, not theory.

"Each of the Big Five dimensions is like a bucket that holds a set of traits that tend to occur together. The definitions of the five super factors represent an attempt to describe the common element among the traits, or sub-factors, within each "bucket." (Howard, 2004) The five factors are:

- **Openness (O)**: refers to the degree to which we are open to new experiences/new ways of doing things, and encompasses four traits (imagination, complexity, change and scope) across a continuum of preserver > moderate > explorer (Howard, 2004). High scorers tend to be original, creative, curious and complex; Low scorers tend to be conventional, down to earth, have narrow interests and be uncreative (John, 2003).
- **Conscientiousness** (C) refers to the degree to which we push toward goals at work, and encompasses five traits (perfectionism, organization, drive, concentration and methodicalness) across a continuum of flexible > balanced > focused (Howard, 2004). High scorers tend to be reliable, well-organized, self-disciplined and careful; Low scorers tend to be disorganized, undependable and negligent (John, 2003).
- **Extraversion (E)**: refers to the degree to which a person can tolerate sensory stimulation from people and situations, and encompasses six traits (enthusiasm, sociability, energy mode, taking charge, trust of others and tact) across a continuum of introvert > ambivert > extravert (Howard, 2004). High scorers tend to be sociable, friendly, fun loving and talkative; Low scorers tend to be introverted, reserved, inhibited and quiet (John, 2003).

- **Agreeableness (A)**: refers to the degree to which we defer to others, and encompasses five traits (service, agreement, deference, reserve and reticence) across a continuum of challenger > negotiator > adapter (Howard, 2004). High scorers tend to be good natured, sympathetic, forgiving and courteous; Low scorers tend to be critical, rude, harsh and callous (John, 2003).
- **Neuroticism (N)**: refers to the degree to which a person responds to stress and encompasses four traits (sensitiveness, intensity, interpretation and rebound time) across a continuum of resilience > responsiveness > reactiveness (Howard, 2004). High scorers tend to be nervous, high-strung, insecure and worriers; Low scorers tend to be calm, relaxed, secure and hardy (John, 2003).

Howard uses slightly different terms to characterize the five factors. He uses originality vice openness, consolidation vice conscientiousness, accommodation vice agreeableness and the need for stability vice neuroticism. Each factor is measured as low (< 45), medium (> 45 and < 55) and high (> 55).

The dimensionality and quantitative nature of FFM provides the ability to represent a finer granularity of personality traits than MBTI. An example of the quantitative nature of FFM is shown in the model's relationship to age. From age 20 to age 30, need for stability, extraversion, and originality tend to decrease, while accommodation and consolidation tend to increase (Howard, 2004). For the purposes of this study, FFM will be utilized as the preference model based on its quantitative characteristics. This research will evaluate independent variables in FFM in regards to their ability to predict the appropriate selection of instructional strategies (specifically media needs).

Statistical studies: Correlations between MBTI and FFM

McCrae and Costa (1989) studied correlations between the MBTI scales and the FFM personality construct. The study was based on the results from 267 men who were followed as part of a longitudinal study of aging. (Similar results were obtained with 201 women.) This data suggests that four of the MBTI scales are related to the FFM personality traits. The correlation study indicates that the MBTI Extraversion-Introversion (E-I) dichotomy has a strong negative correlation with the FFM Extraversion trait and the MBTI Sensing-Intuiting (S-N) dichotomy has a strong positive correlation with the FFM Openness trait. The MBTI Thinking-Feeling (T-F) and Judging-Perceiving (J-P) dichotomies are more weakly related to the FFM Agreeableness and Conscientiousness traits respectively. The neuroticism dimension of the FFM is largely absent from the MBTI.

Split-half reliability of the MBTI scales is good, although test-retest reliability is sensitive to the time between tests. However, because the MBTI dichotomies scores in the middle of the distribution, type allocations are less reliable. Within each scale about 83% of categorizations remain the same when retested within nine months, and around 75% when retested after nine months. About 50% of people tested within nine months remain the same overall type and 36% remain the same after nine months. (Harvey, 1996)

Have there been any studies regarding correlations between personality preferences and learning style preferences? Rosati (1995) published the only correlation study looking at personality preferences and learning style preferences using MBTI and ILS. The MBTI and ILS were administered to the same students and he found:

- Most students that were “sensing” on ILS were also “sensing: on MBTI with the association being highly significant.
- There was a correlation between “active” learning on ILS and “extraversion” on MBTI; “active” learners were significantly more “extraverted” and “perceiving”
- “Sequential” learners in ILS were more likely to be “sensors” than “intuitors” on MBTI

However, these results provide no basis to predict the degree/probability of sensing behavior in a “sensing” learner based on being an MBTI sensor since MBTI does not measure the degree of sensing.

<u>Gaps: Specific Research Questions that have not been addressed</u>

- Specifically, how do FFM personality preference variables (i.e. openness, conscientiousness…) relate to ILS learning style preferences (i.e. visual, sequential, reflective…)?
- Is there a strong correlation?
- Can a dependency between any two variables be established?
- Are FFM personality preferences variables good predictors of learning style preferences?

Proposed Concept: Models, Approaches and Techniques

Proposed Models

The FFM variables will be used (vice MBTI) for the experimentation and analysis proposed in this thesis since their construct validity and predictive validity is not in question. The FFM instrument is conveniently available online at http://www.outofservice.com/bigfive/

The Index of Learning Styles (ILS) will be used for the experimentation and analysis proposed in this thesis. This selection is based on reliability, the validity of the instrument and the convenience of taking the instrument online.

What is known about the reliability and validity of the ILS? Three studies have examined the independence, reliability, and construct validity of the four instrument scales. The authors (Felder and Spurlin, 2005; Zywno, 2003; Litzinger, et al, 2005) concluded that the ILS meets standard acceptability criteria for instruments of its type.

The factor analysis conducted shows the eight factors, corresponding scales and questionnaire items shown in Table 2.

Table 2: Factors in the Eight Factor Solution (Litzinger, 2005)

Scale	#F	Items	Factors
Sensing - Intuitive	1	38, 6, 18, 14, 2, 10, 34 26, 22, ***42, 30***	Preference for concrete information (facts, data, the "real world") or abstraction (interpretations, theories, models)
Visual - Verbal	2	7, 31, 23, 11, 15	Information format preferred for input
	5	27, 19, 3, 35, 43, ***39***	Information format preferred for memory or recall
Sequential - Global	3	20, 36, 44, 8, 12, 32, 24	Linear/sequential or random/holistic thinking
	8	28, 4, 16, ***40***	Emphasize details (the trees) or the big picture (the forest)
Active - Reflective	4	25, 1, 29, 5, 17	Action-first or reflection-first
	6	37, 13, 9	Outgoing or reserved
	7	21, 33, 41	Favorable or unfavorable attitude toward group work

The result of the factor analysis is shown in Table 3. The factor analysis, combined with the estimates of reliability, provides evidence of construct validity for the ILS.

Table 3: ILS Factor Analysis (Litzinger, 2005)

SCALE	ITEM	FACTORS							
		1	2	3	4	5	6	7	8
Active / Reflective	25	.	.	.	**0.68**	.	.	.	.
	1	.	0.23	.	**0.67**	0.11	.	.	.
	29	0.23	0.18	.	**0.53**	0.22	.	.	.
	5	.	-0.16	.	**0.43**	.	0.31	0.26	.
	17*	.	-0.14	.	**0.42**	.	-0.40	.	.
	13	.	.	.	0.11	.	**0.59**	0.17	.
	37	-0.10	-0.12	-0.17	0.24	.	**0.56**	0.21	.
	9	-0.23	.	.	.	.	**0.50**	.	.
	41	0.22	.	.	.	.	.	**0.63**	0.10
	21	.	0.15	.	.	.	0.20	**0.61**	.
	33	.	.	.	.	.	0.14	**0.60**	.
Sequential / Global	20	0.26	.	**0.53**	.	.	-0.11	.	0.19
	36	0.20	.	**0.52**	.	-0.12	.	0.11	0.22
	44	0.14	.	**0.50**	0.10	.	.	.	.
	8	.	.	**0.46**	.	0.23	.	0.12	0.34
	12	.	.	**0.43**	.	.	0.28	-0.18	.
	32	.	.	**0.42**	.	.	.	0.14	-0.32
	24	0.13	.	**0.40**	-0.22	0.11	0.22	-0.25	-0.10
	4	.	.	0.15	.	.	.	.	**0.62**
	28	0.13	.	0.21	.	-0.18	.	.	**0.60**
	16	0.18	.	0.11	.	.	0.20	.	**0.36**
	40*	-0.12	.	.	.	.	-0.29	.	**0.12**
Sensing / Intuitive	38	**0.75**	.	0.15	0.13	0.11	.	.	0.17
	6	**0.71**	.	.	0.12	0.20	.	.	.
	18	**0.68**	.	0.20	0.18	.	.	.	.
	14	**0.57**	0.12	.	0.11	-0.19	.	.	0.18
	2	**0.52**	.	0.26	.	.	.	.	-0.28
	10	**0.52**	-0.16	0.11	.	0.17	.	.	0.30
	34	**0.46**	0.12	0.19	-0.15	.	.	.	-0.35
	26	**0.44**	0.18	0.12	-0.14	-0.10	-0.13	0.10	-0.18
	22	**0.35**	.	0.45	-0.19	.	.	-0.19	.
	42*	**0.24**	0.12	0.11	-0.24	.	0.52	-0.18	0.16
	30	**0.21**	-0.13	0.57	.	.	-0.11	.	.
Visual / Verbal	7	.	**0.77**	.	.	0.15	.	.	.
	31	.	**0.70**	.	0.17	0.19	.	.	.
	23	.	**0.66**	-0.17	.	.	.	.	.
	11	.	**0.65**	.	.	0.19	.	0.21	.
	15	.	**0.55**	.	.	0.15	.	.	.
	19	.	0.22	.	.	**0.59**	.	-0.10	.
	35	.	0.17	0.17	0.17	**0.54**	.	.	.
	3	.	0.18	.	.	**0.53**	.	0.15	.
	27	.	0.38	.	.	**0.53**	.	.	.
	43	0.16	.	-0.15	.	**0.50**	.	.	.
	39*	0.35	.	0.10	.	**0.19**	.	0.34	.

Proposed Approaches and Techniques

This thesis proposes a regression analysis for the one-on-one interactions between FFM variables and ILS variables. SEM (structure equation modeling) analysis, which is an extension of a path analysis, will be used to study the patterns of relationships among the several variables that constitute the FFM and the ILS. The SEM analysis will produces a diagram indicating specific manner by which variables are related (i.e., paths) and strength of those relationships. It will also clarify the direct and indirect of relationships among variables based on underlying theoretical constructs. AMOS (Analysis of Moment Structures) 5.0.1, a SEM analysis computer program will be used to conduct this analysis.

CHAPTER THREE: RESEARCH METHODS

Chapter Three Summary

This chapter reviews the research goal for this thesis, a proposed hypothesis and research methods selected for the correlation analysis of variables contained in the FFM and the ILS. The protocol for this study was submitted to the University of Central Florida (UCF) Institutional Review Board (IRB) for approval. The results of their review are in Appendix A.

Research Goal

The primary research goal for this thesis is to investigate relationships between personality preferences, learning style preferences, and learning.

Proposed Hypotheses

The null hypothesis one, H_0 is: There is no dependency between personality preference variables and learning style preference variables. Dependency will be measured by using regression analysis to determine standardized direct effects (also known as correlation coefficients or multiple R) and model fit was determined by the comparative fit index (CFI) using the AMOS structural equation modeling tool. The Microsoft Excel data analysis package and AMOS were used to determine significant correlations of the individual results of both the Big Five Personality Test and the Index of Learning Styles questionnaire. The sub hypotheses tested were:

- Sub null hypothesis H_{0A}: There is no dependency between personality preference variables and the active-reflective learning style preference.

- Sub null hypothesis H_{0B}: There is no dependency between personality preference variables and the sequential-global learning style preference.
- Sub null hypothesis H_{0C}: There is no dependency between personality preference variables and the sensing-intuiting learning style preference.
- Sub null hypothesis H_{0D}: There is no dependency between personality preference variables and the visual-verbal learning style preference.

The alternate hypothesis one, H1 is: There is a dependency between personality preference variables and learning style preference variables.

Model Development and Testing Process

In order to investigate the above hypothesis, research was conducted involving two groups of participants. Seventy-five percent of the sample (75 people) were randomly assigned to Group A and their data was used to support model development. Twenty-five percent were assigned to Group B and their data was used to support model validation. The minimum sample size of seventy-two (72) was selected based on the number of variables (five FFM variables + four ILS variables x eight participants per variable). AMOS, the structural equation modeling tool used in this study, generally calls for fifteen (15) participants per independent variable (five FFM variables * 15 participants per variable = 75 participants). Both groups of participants were randomly drawn from a population of engineering professionals, simulation industry professionals and students in the Greater Orlando, Florida area. The demographics for this group are summarized in Table 4.

Group A test participants will be administered the FFM and ILS online. The correlation data derived through the regression analysis shown in Figure 5 will be used to construct a predictive model for use in an ITS instructional planner.

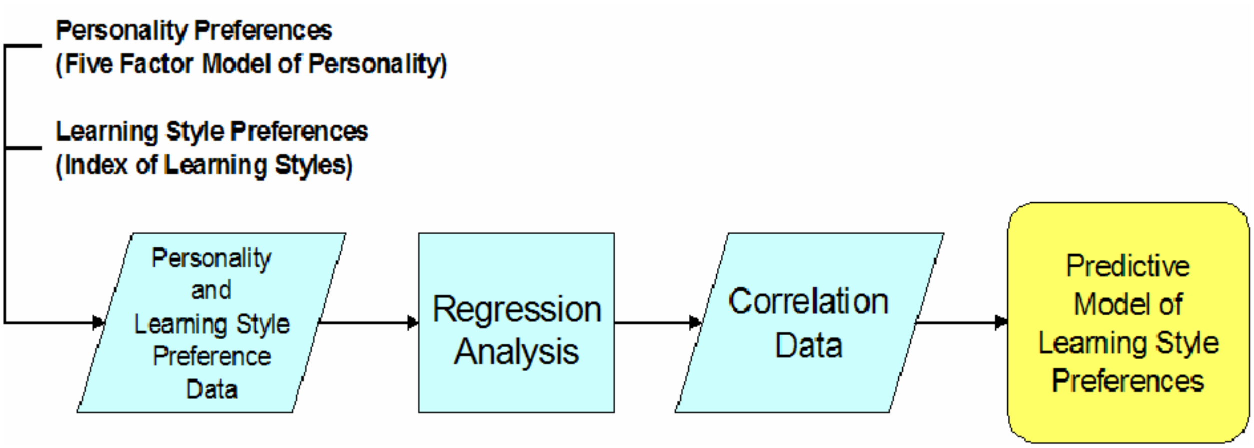

Figure 1: Analysis and Model Development Process

This research will utilize linear regression modeling, but will also use SEM (structural equation modeling) analysis, which is an extension of a path analysis to study the patterns of relationships among the variables that constitute the FFM and the ILS. The SEM analysis produces a diagram indicating the specific manner by which variables are related (i.e. paths) and strength of those relationships. It will also clarify the direct and indirect of relationships among variables based on underlying theoretical constructs. AMOS 5.0.1, a SEM analysis computer program will be used to conduct this analysis. Data from this analysis will be derived from the two instruments (FFM and ILS) consisting of five and four variables respectively. Once the SEM analysis is complete, the correlation data will be used to construct a predictive model for use in an ITS instructional planner. The predictive model will then be tested in an experiment with Group B.

In Group B, the process in **Figure 2** will be used to validate the model developed from Group A's preference data:

- the Group B participants will take FFM online;
- the researcher will take the FFM data and use it as input for the predictive model;
- the researcher will run model which will predict appropriate preferences;
- the participants will be exposed to the training scenario shown in Appendix C;
- the participants will then be queried about the media presented in the training scenario using the media feedback survey in Appendix D to ascertain if the training scenario supported their learning style preferences;
- the predicted learning style preferences (expected results) will be compared with the student's actual learning style preference based on the participant's observations of the media.

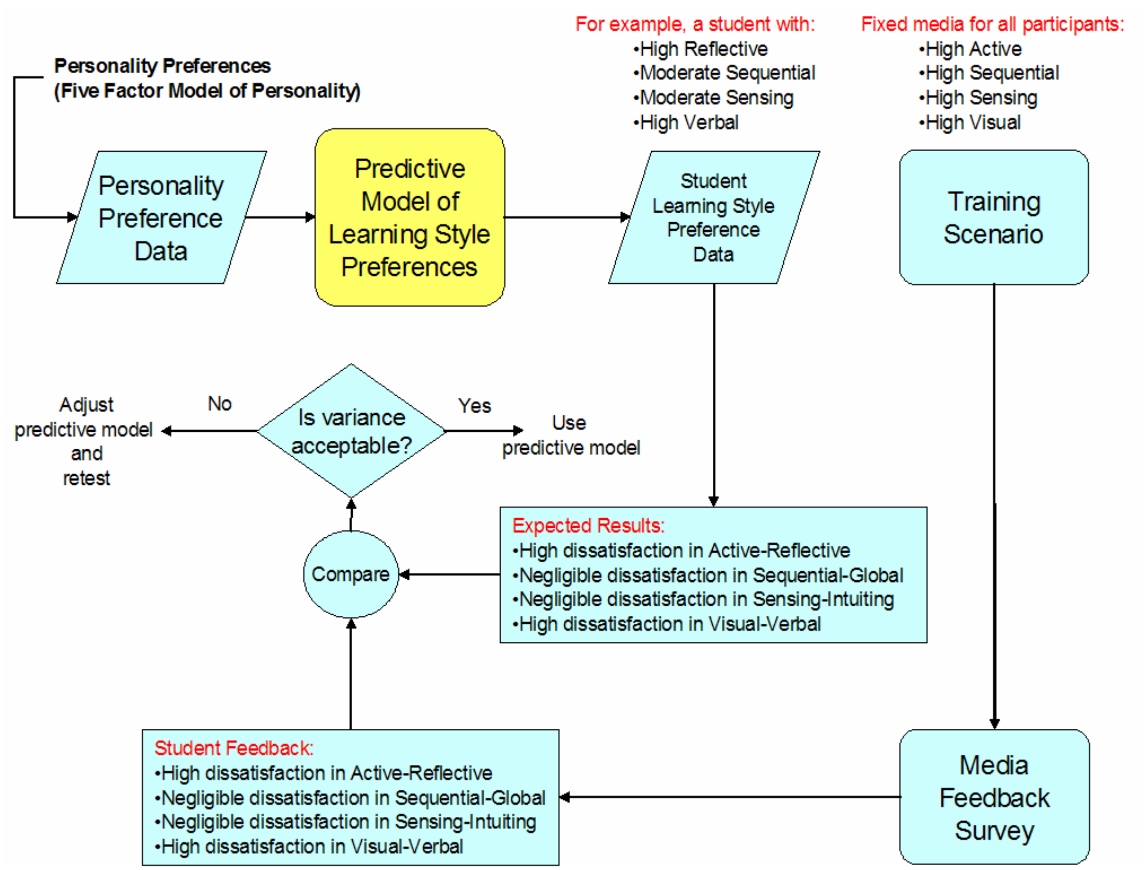

Figure 2: Experimentation Process

Ideally, the variance between the predicted learning style preferences and the participant's actual learning style preference should be small. If it is not, the predictive model will be adjusted and additional participants will be tested as needed to validate the model.

Scope and Limitations of Evaluation

Even a strong correlation between personality preference and learning preference variables does not guarantee an increase in learning. The correct media could be selected and ignored due to lack of motivation, boredom, frustration or another emotion. Additional work is needed to integrate the influences of parameters like motivation and trust into a comprehensive instructional planner that might look like the conceptual model shown in Figure 3. The portion of the model shown within the dotted line is the defined scope for this thesis.

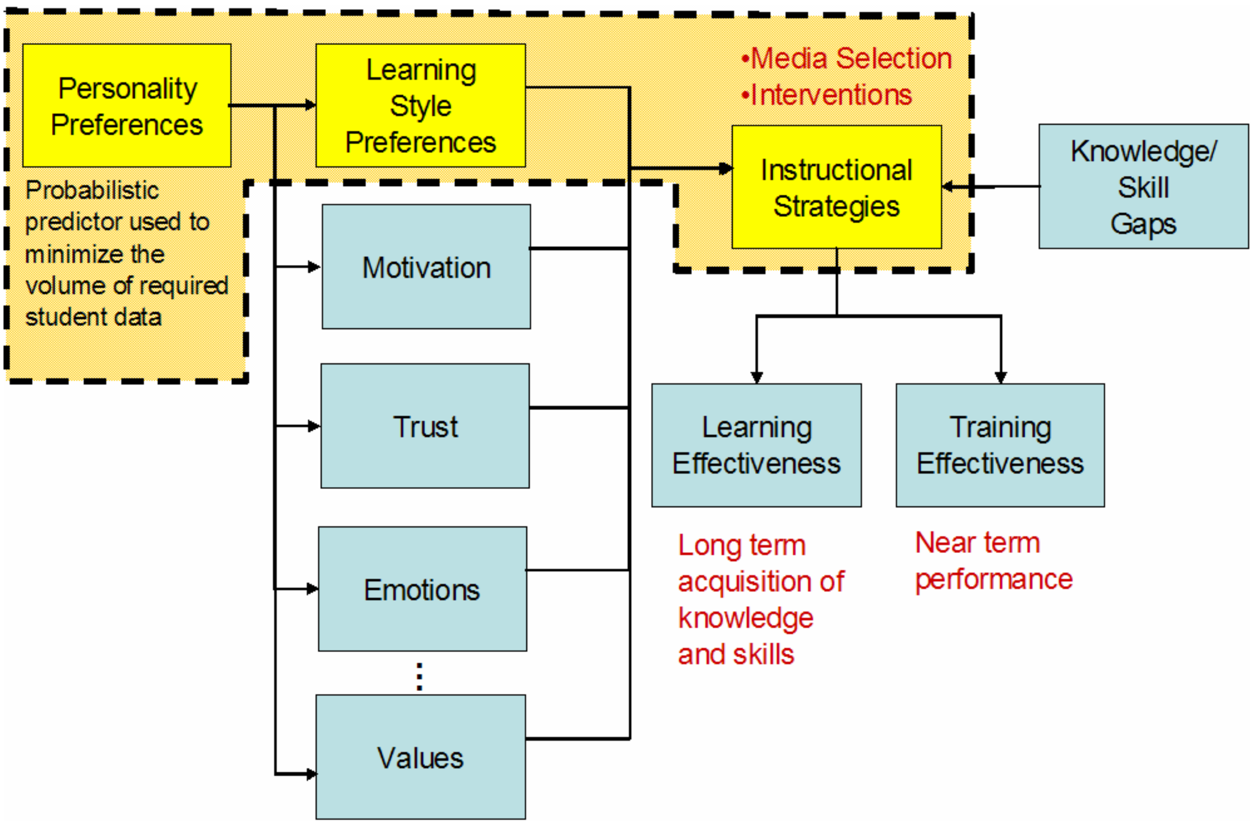

Figure 3: Scope and Limitations of Research

CHAPTER FOUR: DATA AND ANALYSIS

Chapter Four Summary

This chapter reviews the characteristics of the data collected including demographic breakouts and descriptive statistics for the key variables. A regression analysis is conducted. Correlation coefficients are tested for significance. Predictive models are developed based on highly significant correlations and the models are tested to minimize error and are validated by a media feedback survey. The responses of the media feedback survey are analyzed. A structural equation model is constructed and compared to the regression analysis for consistent results.

Data Summary

Group A was comprised of seventy-five randomly selected participants. Group A data was used as the basis for regression analysis and development of a predictive model. Group A provided demographic data via the survey in Appendix E. Group A demographics are shown in

Table 4. Subgroups were used to examine more specific correlations and included two subgroups for age (younger than 30 years old and 30 years old and older), two subgroups for gender (male and female) and three subgroups for educational level (high school graduate without a degree, Bachelors Degree and Masters/PhD). Participants were at least 18 years old.

Table 4: Group A Demographics

Subgroup	Sample Size	% of Sample
All	75	100.0%
Age < 30	35	46.7%
Age ≥ 30	40	53.3%
Male	51	68.0%
Female	24	32.0%
High School Graduate	17	22.7%
Bachelors Degree	34	45.3%
Masters Degree or PhD	24	32.0%
Male and Age < 30	24	32.0%
Female and Age <30	11	14.7%
High School Graduate and Age < 30	15	20.0%
Bachelors Degree and Age < 30	15	20.0%
Masters/PhD and Age <30	5	6.7%
Male and Age ≥ 30	27	36.0%
Female and Age ≥ 30	13	17.3%
High School Graduate and Age ≥ 30	2	2.7%
Bachelors Degree and Age ≥ 30	19	25.3%
Masters/PhD and Age ≥ 30	19	25.3%
Male and High School Graduate	12	16.0%
Male and Bachelors Degree	25	33.3%
Male and Masters/PhD	14	18.7%
Female and High School Graduate	5	6.7%
Female and Bachelors Degree	9	12.0%
Female and Masters/PhD	10	13.3%

Variable data was collected from Group A participants that included the results of the Big Five Personality Test and the Index of Learning Styles. The data was compiled in a spreadsheet and analyzed per the methods described in Chapter Three. Table 5 provides the descriptive statistics for the five independent variables of the Five Factor Model (FFM) collected via the Big Five Personality Test.

Table 5: Descriptive Statistics for the Group A Five Factor Model Variables

Openness		*Conscientiousness*		*Extraversion*	
Mean	43.61333333	Mean	70.17333333	Mean	47.12
Standard Error	3.193794283	Standard Error	2.673687155	Standard Error	3.234997807
Median	47	Median	79	Median	42
Mode	53	Mode	79	Mode	37
Standard Deviation	27.65906984	Standard Deviation	23.15480998	Standard Deviation	28.01590282
Sample Variance	765.0241441	Sample Variance	536.1452252	Sample Variance	784.8908108
Kurtosis	-1.019620748	Kurtosis	0.066941188	Kurtosis	-1.192880256
Skewness	0.220000491	Skewness	-0.842962372	Skewness	0.172979582
Range	94	Range	90	Range	94
Minimum	2	Minimum	8	Minimum	3
Maximum	96	Maximum	98	Maximum	97
Sum	3271	Sum	5263	Sum	3534
Count	75	Count	75	Count	75
Largest(1)	96	Largest(1)	98	Largest(1)	97
Smallest(1)	2	Smallest(1)	8	Smallest(1)	3
Confidence Level (95.0%)	6.363774773	Confidence Level (95.0%)	5.327438577	Confidence Level (95.0%)	6.445874597

Agreeableness		*Neuroticism*	
Mean	55.85333333	Mean	38.4
Standard Error	3.045936199	Standard Error	3.313907359
Median	57	Median	32
Mode	74	Mode	43
Standard Deviation	26.37858126	Standard Deviation	28.69927958
Sample Variance	695.8295495	Sample Variance	823.6486486
Kurtosis	-0.966146999	Kurtosis	-1.086632841
Skewness	-0.347545729	Skewness	0.445771325
Range	95	Range	95
Minimum	1	Minimum	2
Maximum	96	Maximum	97
Sum	4189	Sum	2880
Count	75	Count	75
Largest(1)	96	Largest(1)	97
Smallest(1)	1	Smallest(1)	2
Confidence Level (95.0%)	6.069161075	Confidence Level (95.0%)	6.603105329

Table 6 provides descriptive statistics the four dependent variables of the Felder-Silverman Learning Style Model collected via the Index of Learning Styles (ILS) instrument.

Table 6: Descriptive Statistics for the Group A Index of Learning Styles Data

Active-Reflective		*Sensing-Intuitive*	
Mean	11.2	Mean	9.04
Standard Error	0.609829396	Standard Error	0.663444465
Median	12	Median	10
Mode	12	Mode	12
Standard Deviation	5.281277487	Standard Deviation	5.74559761
Sample Variance	27.89189189	Sample Variance	33.01189189
Kurtosis	-0.5743744	Kurtosis	-0.842805984
Skewness	0.275969315	Skewness	0.129842795
Range	20	Range	20
Minimum	2	Minimum	0
Maximum	22	Maximum	20
Sum	840	Sum	678
Count	75	Count	75
Largest(1)	22	Largest(1)	20
Smallest(1)	2	Smallest(1)	0
Confidence Level (95.0%)	1.215111739	Confidence Level (95.0%)	1.32194211

Visual-Verbal		*Sequential-Global*	
Mean	6.24	Mean	10.4
Standard Error	0.53552702	Standard Error	0.505109033
Median	6	Median	10
Mode	4	Mode	10
Standard Deviation	4.637800038	Standard Deviation	4.374372542
Sample Variance	21.50918919	Sample Variance	19.13513514
Kurtosis	0.446214441	Kurtosis	-0.324811315
Skewness	0.865819946	Skewness	0.063692839
Range	20	Range	20
Minimum	0	Minimum	2
Maximum	20	Maximum	22
Sum	468	Sum	780
Count	75	Count	75
Largest(1)	20	Largest(1)	22
Smallest(1)	0	Smallest(1)	2
Confidence Level (95.0%)	1.067061006	Confidence Level (95.0%)	1.006451837

Data Analysis and Model Development

The first step in the development of a predictive model of learning styles was to conduct a linear regression with the data from the seventy-five participants that make up Group A. Linear regression was conducted pair wise to identify correlations. The linear regression was conducted on the entire sample in Group A and defined subgroups (males, females, age ≥ 30, age <30, high school graduates, Bachelors degree, Masters/PhD degree and combinations of these subgroups). The scatter diagrams with trend lines for the twenty (20) variable pairs (i.e. extraversion vs. sensing-intuitive) are shown in Appendix F.

For each ILS factor (Active-Reflective, Sensing-Intuitive, Visual-Verbal and Sequential-Global) and group/subgroup, the regression equation(s) with the greatest absolute value of slope and standardized direct effect (also known as correlation coefficient and multiple R) was selected to test for significance. Only those highly significant ($p \leq 0.05$) regression equations were used to predict learning styles.

Table 7 through Table 10 show significance tests in blue (high significance with a probability, $p = 0.05$, 0.01 or 0.001) and red (low significance with a $p > 0.05$). The items in gray were not tested for significance since they were not the highest correlated items in the treatment they were in.

The null hypothesis, H_0, asserted that there is no dependency between personality preference variables and learning preference variables. Based on a desired minimum confidence level of 95%, treatments not meeting these criteria were discarded. The correlation coefficient and significance testing provided the criteria to reject the null hypothesis. The results of the regression analysis/significance testing for each treatment are contained in Appendix G.

Table 7: Results of significance testing for predictors of the Active-Reflective scale

	Subgroup	Sample Size	Openness	Conscientiousness	Extraversion	Agreeableness	Neuroticism
Active-Reflective Learning Style	All	75			$p = 0.001$		
	Age < 30	35			$p = 0.001$		
	Age ≥ 30	40			$p = 0.001$		
	Male	51			$p = 0.001$		
	Female	24			$p = 0.01$		
	High School Graduate	17			$p = 0.01$		
	Bachelors Degree	34			$p = 0.001$		
	Masters Degree or PhD	24			$p = 0.001$		

Referencing Table 7, there are highly significant correlations between extraversion (E) and the active-reflective (AR) learning style scale. All eight treatments tested demonstrated high significance at a probability, $p \leq 0.01$ (confidence level ≥ 99%).

Openness, conscientiousness, agreeableness and neuroticism had lower correlations and therefore, were not as significant of a predictor of the AR learning style as extraversion. The sub null hypothesis, $H_{0A,}$ asserted that there is no dependency between the personality preference variables and the AR learning style preference variable. This sub null hypothesis can be rejected.

Table 8: Results of significance testing for predictors of the Sensing-Intuitive scale

	Subgroup	Sample Size	Openness	Conscientiousness	Extraversion	Agreeableness	Neuroticism
Sensing-Intuitive Learning Style	All	75	$p = 0.001$				
	Age < 30	35			$p = 0.05$		
	Age ≥ 30	40	$p = 0.001$				
	Male	51	$p = 0.01$				
	Female	24	$p = 0.01$				
	High School Graduate	17					
	Bachelors Degree	34	$p = 0.01$				
	Masters Degree or PhD	24					

Referencing Table 8, there are highly significant correlations between openness (O) and the sensing-intuitive (SI) learning style scale. Six (6) of the eight treatments tested demonstrated high significance at a probability, $p \leq 0.01$ (confidence level ≥ 99%). The two (2) other treatments tested were determined to have low significance in relationship to our criteria and were not used as production rules in our cognitive model. Conscientiousness, agreeableness and neuroticism had lower correlations and therefore, were not as significant of a predictor of the SI learning style as openness and extraversion.

Table 9: Results of significance testing for predictors of the Visual-Verbal scale

	Subgroup	Sample Size	Openness	Conscientiousness	Extraversion	Agreeableness	Neuroticism
Visual-Verbal Learning Style	All	75					
	Age < 30	35					
	Age ≥ 30	40	p = 0.05				
	Male	51					
	Female	24			p = 0.05		
	High School Graduate	17					
	Bachelors Degree	34					
	Masters Degree or PhD	24	p = 0.05				

Referencing Table 9, there are three (3) of eight (8) treatments tested that demonstrated highly significant correlations between openness (O) and the visual-verbal (VV) learning style scale. One (1) of the treatments tested demonstrated a highly significant correlation between extraversion (E) and the visual-verbal learning style scale. The remaining five (5) treatments tested were determined to have low significance in relationship to our criteria. Conscientiousness, agreeableness and neuroticism had lower correlations and therefore, were not as significant of a predictor of the VV learning style as openness and extraversion.

Table 10: Results of significance testing for predictors of the Sequential-Global scale

	Subgroup	Sample Size	Openness	Conscientiousness	Extraversion	Agreeableness	Neuroticism
Sequential-Global Learning Style	All	75					
	Age < 30	35					
	Age ≥ 30	40					
	Male	51					
	Female	24					
	High School Graduate	17					
	Bachelors Degree	34	p = 0.05				
	Masters Degree or PhD	24					

Referencing Table 10, there was only one (1) of ten (10) treatments that demonstrated highly significant correlations between any of the five factors and the sequential-global (SG) learning style scale. The Bachelors Degree subgroup was determined to have a highly significant correlation between openness (O) and the sequential-global learning style. The remaining nine (9) other treatments tested were determined to have low significance in relationship to our criteria. Conscientiousness, extraversion, agreeableness and neuroticism had lower correlations and therefore, were not as significant of a predictor of the SG learning style as openness.

Based on the results of the significance testing, null hypotheses noted in Table 11 were rejected since it was determined that highly significant relationships exist between these variables.

Table 11: Rejection of the Null Hypotheses

Reject H_0 ?		Learning Style Preferences			
		Active-Reflective	Sensing-Intuitive	Visual-Verbal	Sequential-Global
Five Factor Model	Openness		Reject H_0	Reject H_0	Reject H_0
	Conscientiousness				
	Extraversion	Reject H_0	Reject H_0	Reject H_0	
	Agreeableness				
	Neuroticism				

Based on the significant correlations noted above, a predictive model was developed using the mathematical relationships from the regression analysis as "production rules" to predict learning style preferences. As a basis, the regression equation of each treatment (i.e. AR predicted by E) is used. Again, only the equations that provide a 95% or greater confidence level are used in the model.

The mathematical equation for the regression equation with the best fit for AR predicted by E is:

Equation 1: AR = slope * E + b

$$AR = slope * E + b$$

A regression line was calculated for each significant treatment and multiple predictions of AR are generated in the model. To weight the impact of each linear regression calculation, each of the predicted AR values is multiplied by the confidence level and then summed. The result is divided by the sum of the confidence levels as shown in Equation 2. This equation was also applied to the other models for SI, VV and SG learning style preferences.

Equation 2: Predictive Model for i significant treatments

$$\text{AR Predicted} = \sum (AR_i * Confidence_i)/\sum Confidence_i$$

Next, the predictive model was tested against the known data in Group A to detect and minimize errors. Once the errors were minimized for the set of Group A data, the predictive model was then applied to the Group B data to predict learning styles and validate/invalidate the model.

Predictive Models

Since most of the population (67%) demonstrates a preference for the “active” learning style preference (Montgomery, 1995), the predictive model for AR was setup to only select “reflective” when the calculations demonstrated a very clear preference for the reflective learning style. The predictive model for AR was set up to select the “reflective” learning style preference when the “AR Predicted” value is greater than 14.436. This value provided the minimum error and was derived from the mean of AR plus or minus the average error computed for Group A. The average numerical error between the predicted values and the actual values for Group A was 3.236. Since the mean of AR is 11.2, this yields two values 7.964 and 14.436.

Any computed value of AR > 14.436 and < 7.964 is less ambiguous and is more clearly "reflective" or "active" respectively. Any ambiguous values (7.964 > AR >14.436) are assumed to be "active" based on expected population norms.

The AR predictive model (based on Group A data) output an error (selected the wrong learning style) 20% of the time. This was also the expected error rate for Group B, the model validation group. In actuality, Group B output an error 16% of the time with an average numerical error of only 1.207 vice 3.236 in Group A. These error rates are significantly lower than the expected 33% error rate that would have been realized if the only choice was "active". The predictive results for the refined model based on Group A data are shown in Table 12.

Table 12: Group A results for predicting Active-Reflective learning style preferences

Participant	Predicted AR	Predicted Learning Style	Actual Learning Style	Error Count	Numerical Error	Participant	Predicted AR	Predicted Learning Style	Actual Learning Style	Error Count	Numerical Error
1	11.722	Active	Active	0	5.722	40	12.722	Active	Active	0	1.278
2	5.529	Active	Active	0	6.471	41	8.124	Active	Active	0	1.876
3	7.353	Active	Active	0	4.647	42	11.769	Active	Active	0	1.769
4	14.313	Active	Reflective	1	7.687	43	15.165	Reflective	Active	1	7.165
5	9.829	Active	Active	0	5.829	44	16.925	Reflective	Reflective	0	5.075
6	12.370	Active	Active	0	2.370	45	12.361	Active	Active	0	1.639
7	8.092	Active	Active	0	4.092	46	8.436	Active	Reflective	1	7.564
8	13.033	Active	Active	0	0.967	47	15.655	Reflective	Reflective	0	4.345
9	15.904	Reflective	Active	1	3.904	48	13.147	Active	Active	0	9.147
10	14.947	Reflective	Active	1	0.947	49	5.317	Active	Active	0	2.683
11	5.773	Active	Active	0	4.227	50	8.302	Active	Active	0	1.698
12	8.092	Active	Active	0	0.092	51	14.944	Reflective	Active	1	6.944
13	6.286	Active	Active	0	0.286	52	12.361	Active	Active	0	1.639
14	7.888	Active	Active	0	3.888	53	10.778	Active	Active	0	4.778
15	10.270	Active	Active	0	2.270	54	6.139	Active	Active	0	2.139
16	16.644	Reflective	Reflective	0	3.356	55	11.717	Active	Active	0	0.283
17	8.873	Active	Active	0	2.873	56	13.535	Active	Active	0	5.535
18	16.256	Reflective	Reflective	0	5.744	57	10.483	Active	Active	0	0.483
19	13.952	Active	Active	0	0.048	58	13.066	Active	Active	0	3.066
20	14.770	Reflective	Active	1	4.770	59	13.859	Active	Active	0	1.859
21	8.366	Active	Active	0	3.634	60	9.435	Active	Active	0	1.435
22	10.298	Active	Active	0	0.298	61	9.778	Active	Active	0	4.222
23	6.568	Active	Active	0	1.432	62	8.491	Active	Active	0	1.510
24	5.614	Active	Active	0	2.386	63	12.121	Active	Active	0	0.121
25	12.556	Active	Active	0	0.556	64	4.796	Active	Active	0	2.796
26	14.831	Reflective	Reflective	0	3.169	65	12.306	Active	Active	0	4.306
27	14.806	Reflective	Active	1	2.806	66	10.717	Active	Active	0	1.283
28	9.435	Active	Active	0	5.435	67	8.096	Active	Active	0	5.904
29	14.034	Active	Reflective	1	1.966	68	11.124	Active	Active	0	0.876
30	15.542	Reflective	Active	1	1.542	69	14.831	Reflective	Active	1	0.831
31	12.361	Active	Reflective	1	5.639	70	12.361	Active	Active	0	1.639
32	14.662	Reflective	Reflective	0	7.338	71	7.604	Active	Active	0	1.604
33	8.124	Active	Active	0	4.124	72	6.139	Active	Active	0	4.139
34	17.051	Reflective	Reflective	0	0.949	73	10.778	Active	Reflective	1	7.222
35	15.965	Reflective	Reflective	0	4.035	74	7.361	Active	Active	0	3.361
36	15.920	Reflective	Active	1	3.920	75	5.117	Active	Active	0	3.117
37	15.542	Reflective	Reflective	0	2.458				Group A Errors =	15	242.67
38	6.993	Active	Active	0	0.993				Group A % Error =	20.00%	3.236
39	13.531	Active	Reflective	1	4.469						

Table 13: Group B results for predicting Active-Reflective learning style preferences

Participant	Predicted AR	Predicted Learning Style	Actual Learning Style	Error Count	Numerical Error
1	5.731	Active	Active	0	2.269
2	11.717	Active	Active	0	2.283
3	14.025	Active	Active	0	6.025
4	5.111	Active	Active	0	6.889
5	11.844	Active	Active	0	1.844
6	4.700	Active	Active	0	1.300
7	8.363	Active	Active	0	3.637
8	7.209	Active	Active	0	4.791
9	12.059	Active	Reflective	1	7.941
10	14.025	Active	Active	0	4.025
11	6.412	Active	Active	0	0.412
12	10.298	Active	Active	0	3.702
13	6.452	Active	Active	0	0.452
14	15.655	Reflective	Reflective	0	4.345
15	7.816	Active	Active	0	0.184
16	10.748	Active	Reflective	1	5.252
17	15.707	Reflective	Reflective	0	2.293
18	13.406	Active	Active	0	3.406
19	16.256	Reflective	Active	1	6.256
20	14.436	Active	Active	0	4.436
21	5.529	Active	Active	0	2.471
22	14.469	Reflective	Reflective	0	1.531
23	13.501	Active	Reflective	1	4.499
24	14.313	Active	Active	0	0.313
25	13.952	Active	Active	0	9.952
			Group B Errors =	4	90.511
			Group B % Error =	16.00%	1.207

The model development and validation process involved implementing the AR model developed from Group A data with Group B FFM inputs to predict learning styles. Group B results are shown in Table 13. Group B also provided ILS inputs to aid in model validation.

Table 14: Group A results for predicting Sensing-Intuitive learning style preferences

Participant	Predicted SI	Predicted Learning Style	Actual Learning Style	Error Count	Numerical Error
1	5.141	Sensing	Sensing	0	5.141
2	8.167	Sensing	Sensing	0	8.167
3	14.774	Intuitive	Sensing	1	2.774
4	6.911	Sensing	Sensing	0	1.089
5	11.821	Sensing	Sensing	0	2.179
6	10.746	Sensing	Intuitive	1	9.254
7	12.188	Sensing	Sensing	0	2.188
8	6.682	Sensing	Intuitive	1	9.318
9	5.768	Sensing	Sensing	0	4.232
10	11.136	Sensing	Sensing	0	2.864
11	5.911	Sensing	Sensing	0	5.911
12	5.911	Sensing	Sensing	0	0.089
13	4.976	Sensing	Sensing	0	4.976
14	14.676	Intuitive	Sensing	1	2.676
15	10.154	Sensing	Intuitive	1	7.846
16	9.566	Sensing	Sensing	0	7.566
17	13.795	Sensing	Sensing	0	1.795
18	6.911	Sensing	Sensing	0	2.911
19	9.932	Sensing	Sensing	0	3.932
20	5.197	Sensing	Sensing	0	3.197
21	14.676	Intuitive	Intuitive	0	3.324
22	7.895	Sensing	Intuitive	1	10.105
23	8.174	Sensing	Sensing	0	2.174
24	11.136	Sensing	Sensing	0	7.136
25	9.220	Sensing	Sensing	0	2.780
26	5.928	Sensing	Sensing	0	3.928
27	14.052	Intuitive	Intuitive	0	5.948
28	9.344	Sensing	Sensing	0	3.344
29	6.835	Sensing	Sensing	0	4.835
30	10.073	Sensing	Sensing	0	1.927
31	6.272	Sensing	Sensing	0	5.728
32	7.203	Sensing	Sensing	0	2.797
33	8.710	Sensing	Sensing	0	0.710
34	9.272	Sensing	Sensing	0	1.272
35	8.046	Sensing	Sensing	0	4.046
36	11.527	Sensing	Sensing	0	7.527
37	7.325	Sensing	Sensing	0	1.325
38	7.544	Sensing	Sensing	0	3.544
39	8.168	Sensing	Sensing	0	4.168
40	8.787	Sensing	Sensing	0	1.213
41	8.710	Sensing	Sensing	0	1.290
42	6.896	Sensing	Intuitive	1	9.104
43	8.675	Sensing	Sensing	0	3.325
44	8.918	Sensing	Sensing	0	5.082
45	10.127	Sensing	Sensing	0	4.127
46	6.337	Sensing	Sensing	0	4.337
47	4.654	Sensing	Sensing	0	4.654
48	10.156	Sensing	Sensing	0	4.156
49	11.407	Sensing	Sensing	0	3.407
50	8.143	Sensing	Sensing	0	1.857
51	11.145	Sensing	Intuitive	1	4.855
52	5.939	Sensing	Sensing	0	6.061
53	11.600	Sensing	Intuitive	1	6.400
54	13.856	Sensing	Intuitive	1	4.144
55	11.821	Sensing	Intuitive	1	6.179
56	11.254	Sensing	Sensing	0	1.254
57	9.121	Sensing	Sensing	0	0.879
58	9.407	Sensing	Sensing	0	0.593
59	10.481	Sensing	Sensing	0	2.481
60	9.932	Sensing	Sensing	0	2.068
61	10.173	Sensing	Sensing	0	2.173
62	10.070	Sensing	Sensing	0	0.070
63	7.088	Sensing	Sensing	0	4.912
64	9.932	Sensing	Sensing	0	2.068
65	8.140	Sensing	Sensing	0	4.140
66	7.280	Sensing	Sensing	0	3.280
67	7.305	Sensing	Intuitive	1	12.695
68	6.818	Sensing	Sensing	0	3.182
69	5.436	Sensing	Sensing	0	6.564
70	11.124	Sensing	Sensing	0	1.124
71	5.715	Sensing	Sensing	0	5.715
72	9.344	Sensing	Sensing	0	9.344
73	6.304	Sensing	Sensing	0	0.304
74	8.484	Sensing	Sensing	0	8.484
75	11.336	Sensing	Intuitive	1	6.664
			Group A Errors =	13.00	312.91
			Group A % Error =	17%	4.172

The same process was followed with the Group A data to develop a predictive model for SI and then the model was validated against data from Group B. Results for the Group A data are shown in Table 14 and Group B results are shown in Table 15. About five (5) out of every six (6) participants were correctly predicted to either be “sensing” or “intuitive”.

Table 15: Group B results for predicting Sensing-Intuitive learning style preferences

Participant	Predicted SI	Predicted Learning Style	Actual Learning Style	Error Count	Numerical Error
1	7.139	Sensing	Sensing	0	0.861
2	11.821	Sensing	Sensing	0	5.821
3	8.855	Sensing	Sensing	0	1.145
4	8.682	Sensing	Sensing	0	5.318
5	6.406	Sensing	Sensing	0	1.594
6	7.368	Sensing	Sensing	0	7.368
7	12.684	Sensing	Sensing	0	1.316
8	6.997	Sensing	Sensing	0	3.003
9	11.342	Sensing	Sensing	0	0.658
10	11.042	Sensing	Intuitive	1	4.958
11	11.828	Sensing	Sensing	0	2.172
12	7.895	Sensing	Sensing	0	7.895
13	8.395	Sensing	Sensing	0	0.395
14	4.654	Sensing	Sensing	0	4.654
15	7.305	Sensing	Sensing	0	3.305
16	8.813	Sensing	Sensing	0	2.813
17	8.444	Sensing	Sensing	0	2.444
18	6.125	Sensing	Intuitive	1	13.875
19	5.141	Sensing	Sensing	0	0.859
20	7.169	Sensing	Intuitive	1	8.831
21	13.267	Sensing	Sensing	0	11.267
22	9.080	Sensing	Sensing	0	4.920
23	8.280	Sensing	Sensing	0	3.720
24	6.715	Sensing	Sensing	0	0.715
25	13.757	Sensing	Intuitive	1	2.243
			Group B Errors =	4	102.149
			Group B % Error =	16.00%	1.362

Only three (3) highly significant relationships were used to try to predict VV learning style preferences. The three (3) production rules (predictive relationships) included relationships to characteristics that included age ≥ 30, female and Masters/PhD. This left out some participants who were either age < 30, males, high school graduates or had Bachelors degrees. There were insufficient productions rules to reach a prediction for each participant (in either

Group A or Group B). The results are shown in Table 16 for Group A and Table 17 for Group B.

Table 16: Group A results for predicting Visual-Verbal learning style preferences

Participant	Predicted VV	Predicted Learning Style	Actual Learning Style	Error Count	Numerical Error	Participant	Predicted VV	Predicted Learning Style	Actual Learning Style	Error Count	Numerical Error
1	10.340	Visual	Visual	0	2.340	40	7.158	Visual	Visual	0	3.158
2	7.669	Visual	Visual	0	2.331	41	#DIV/0!	#DIV/0!	Visual	#DIV/0!	#DIV/0!
3	4.143	Visual	Visual	0	0.143	42	6.855	Visual	Visual	0	1.145
4	9.019	Visual	Verbal	1	6.981	43	#DIV/0!	#DIV/0!	Visual	#DIV/0!	#DIV/0!
5	5.748	Visual	Visual	0	0.252	44	#DIV/0!	#DIV/0!	Visual	#DIV/0!	#DIV/0!
6	6.156	Visual	Visual	0	5.844	45	#DIV/0!	#DIV/0!	Visual	#DIV/0!	#DIV/0!
7	4.938	Visual	Visual	0	0.938	46	4.916	Visual	Visual	0	0.916
8	8.411	Visual	Visual	0	0.411	47	9.449	Visual	Visual	0	2.551
9	9.350	Visual	Verbal	1	6.650	48	6.597	Visual	Visual	0	6.597
10	7.105	Visual	Visual	0	3.105	49	#DIV/0!	#DIV/0!	Visual	#DIV/0!	#DIV/0!
11	9.201	Visual	Visual	0	7.201	50	5.868	Visual	Visual	0	5.868
12	9.201	Visual	Visual	0	9.201	51	#DIV/0!	#DIV/0!	Visual	#DIV/0!	#DIV/0!
13	3.764	Visual	Visual	0	1.764	52	#DIV/0!	#DIV/0!	Visual	#DIV/0!	#DIV/0!
14	4.301	Visual	Visual	0	0.301	53	5.338	Visual	Visual	0	1.338
15	6.329	Visual	Visual	0	2.329	54	3.806	Visual	Visual	0	0.194
16	7.037	Visual	Visual	0	1.037	55	6.179	Visual	Visual	0	2.179
17	3.881	Visual	Visual	0	2.119	56	#DIV/0!	#DIV/0!	Visual	#DIV/0!	#DIV/0!
18	9.019	Visual	Verbal	1	6.981	57	#DIV/0!	#DIV/0!	Verbal	#DIV/0!	#DIV/0!
19	6.470	Visual	Visual	0	5.530	58	#DIV/0!	#DIV/0!	Visual	#DIV/0!	#DIV/0!
20	8.922	Visual	Visual	0	1.079	59	5.373	Visual	Visual	0	5.373
21	4.400	Visual	Visual	0	0.400	60	6.470	Visual	Visual	0	6.470
22	8.285	Visual	Verbal	1	11.715	61	#DIV/0!	#DIV/0!	Visual	#DIV/0!	#DIV/0!
23	5.929	Visual	Visual	0	2.071	62	4.844	Visual	Visual	0	3.156
24	5.185	Visual	Visual	0	6.815	63	8.402	Visual	Visual	0	4.402
25	7.234	Visual	Visual	0	0.766	64	6.470	Visual	Visual	0	2.470
26	9.753	Visual	Visual	0	0.247	65	7.158	Visual	Visual	0	7.158
27	3.673	Visual	Visual	0	3.673	66	7.211	Visual	Visual	0	1.211
28	6.870	Visual	Visual	0	7.130	67	8.725	Visual	Visual	0	8.725
29	#DIV/0!	#DIV/0!	Visual	#DIV/0!	#DIV/0!	68	6.491	Visual	Visual	0	2.491
30	#DIV/0!	#DIV/0!	Visual	#DIV/0!	#DIV/0!	69	10.120	Visual	Visual	0	0.120
31	#DIV/0!	#DIV/0!	Visual	#DIV/0!	#DIV/0!	70	#DIV/0!	#DIV/0!	Visual	#DIV/0!	#DIV/0!
32	#DIV/0!	#DIV/0!	Visual	#DIV/0!	#DIV/0!	71	9.334	Visual	Visual	0	9.334
33	#DIV/0!	#DIV/0!	Visual	#DIV/0!	#DIV/0!	72	6.870	Visual	Visual	0	0.870
34	#DIV/0!	#DIV/0!	Visual	#DIV/0!	#DIV/0!	73	8.934	Visual	Visual	0	5.066
35	8.855	Visual	Visual	0	3.145	74	4.370	Visual	Visual	0	3.630
36	#DIV/0!	#DIV/0!	Visual	#DIV/0!	#DIV/0!	75	5.716	Visual	Visual	0	1.716
37	#DIV/0!	#DIV/0!	Visual	#DIV/0!	#DIV/0!				Group A Errors =	#DIV/0!	#DIV/0!
38	#DIV/0!	#DIV/0!	Visual	#DIV/0!	#DIV/0!				Group A % Error =	#DIV/0!	#DIV/0!
39	#DIV/0!	#DIV/0!	Visual	#DIV/0!	#DIV/0!						

Although the three (3) predictors were statistically significant, they were impractical as a model to predict VV learning style preferences.

Table 17: Group B results for predicting Visual-Verbal learning style preferences

Participant	Predicted VV	Predicted Learning Style	Actual Learning Style	Error Count	Numerical Error
1	6.083	Visual	Visual	0	1.917
2	6.179	Visual	Visual	0	0.179
3	#DIV/0!	#DIV/0!	Visual	#DIV/0!	#DIV/0!
4	#DIV/0!	#DIV/0!	Visual	#DIV/0!	#DIV/0!
5	11.364	Visual	Visual	0	7.364
6	9.426	Visual	Visual	0	9.426
7	5.048	Visual	Visual	0	3.048
8	#DIV/0!	#DIV/0!	Visual	#DIV/0!	#DIV/0!
9	#DIV/0!	#DIV/0!	Visual	#DIV/0!	#DIV/0!
10	#DIV/0!	#DIV/0!	Visual	#DIV/0!	#DIV/0!
11	5.349	Visual	Visual	0	3.349
12	8.285	Visual	Visual	0	6.285
13	6.403	Visual	Visual	0	2.403
14	9.449	Visual	Visual	0	1.449
15	4.734	Visual	Visual	0	2.734
16	#DIV/0!	#DIV/0!	Visual	#DIV/0!	#DIV/0!
17	8.733	Visual	Visual	0	3.267
18	9.606	Visual	Visual	0	2.394
19	10.340	Visual	Visual	0	6.340
20	8.491	Visual	Visual	0	5.509
21	4.206	Visual	Visual	0	1.794
22	7.791	Visual	Visual	0	1.791
23	#DIV/0!	#DIV/0!	Visual	#DIV/0!	#DIV/0!
24	9.166	Visual	Visual	0	3.166
25	3.873	Visual	Visual	0	0.127
			Group B Errors =	#DIV/0!	#DIV/0!
			Group B % Error =	#DIV/0!	#DIV/0!

Only one (1) highly significant relationship was used to try to predict SG learning style preferences. The only production rule (predictive relationships) included a relationship between participants who held a Bachelors Degree and the SG learning style (either sequential or global). This left out predictors for a large number of participants who were outside the Bachelors Degree subgroup. There were insufficient productions rules to reach a prediction for each participant (in either Group A or Group B). The results are shown in Table 18 for Group A and Table 19 for Group B.

Table 18: Group A results for predicting Sequential-Global learning style preferences

Participant	Predicted SG	Predicted Learning Style	Actual Learning Style	Error Count	Numerical Error
1	#DIV/0!	#DIV/0!	Sequential	#DIV/0!	#DIV/0!
2	8.888	Sequential	Sequential	0	6.888
3	12.158	Sequential	Sequential	0	2.158
4	#DIV/0!	#DIV/0!	Global	#DIV/0!	#DIV/0!
5	#DIV/0!	#DIV/0!	Sequential	#DIV/0!	#DIV/0!
6	#DIV/0!	#DIV/0!	Global	#DIV/0!	#DIV/0!
7	11.122	Sequential	Sequential	0	1.122
8	#DIV/0!	#DIV/0!	Sequential	#DIV/0!	#DIV/0!
9	#DIV/0!	#DIV/0!	Sequential	#DIV/0!	#DIV/0!
10	#DIV/0!	#DIV/0!	Global	#DIV/0!	#DIV/0!
11	7.634	Sequential	Sequential	0	5.634
12	7.634	Sequential	Sequential	0	5.634
13	7.198	Sequential	Sequential	0	5.198
14	#DIV/0!	#DIV/0!	Sequential	#DIV/0!	#DIV/0!
15	9.869	Sequential	Sequential	0	2.132
16	#DIV/0!	#DIV/0!	Sequential	#DIV/0!	#DIV/0!
17	#DIV/0!	#DIV/0!	Sequential	#DIV/0!	#DIV/0!
18	#DIV/0!	#DIV/0!	Sequential	#DIV/0!	#DIV/0!
19	9.869	Sequential	Global	1	6.132
20	#DIV/0!	#DIV/0!	Sequential	#DIV/0!	#DIV/0!
21	#DIV/0!	#DIV/0!	Sequential	#DIV/0!	#DIV/0!
22	#DIV/0!	#DIV/0!	Sequential	#DIV/0!	#DIV/0!
23	8.888	Sequential	Sequential	0	1.113
24	#DIV/0!	#DIV/0!	Sequential	#DIV/0!	#DIV/0!
25	#DIV/0!	#DIV/0!	Sequential	#DIV/0!	#DIV/0!
26	#DIV/0!	#DIV/0!	Sequential	#DIV/0!	#DIV/0!
27	12.158	Sequential	Global	1	3.843
28	9.542	Sequential	Sequential	0	0.458
29	#DIV/0!	#DIV/0!	Sequential	#DIV/0!	#DIV/0!
30	#DIV/0!	#DIV/0!	Sequential	#DIV/0!	#DIV/0!
31	7.362	Sequential	Sequential	0	3.362
32	#DIV/0!	#DIV/0!	Sequential	#DIV/0!	#DIV/0!
33	#DIV/0!	#DIV/0!	Sequential	#DIV/0!	#DIV/0!
34	#DIV/0!	#DIV/0!	Sequential	#DIV/0!	#DIV/0!
35	#DIV/0!	#DIV/0!	Sequential	#DIV/0!	#DIV/0!
36	#DIV/0!	#DIV/0!	Sequential	#DIV/0!	#DIV/0!
37	#DIV/0!	#DIV/0!	Sequential	#DIV/0!	#DIV/0!
38	#DIV/0!	#DIV/0!	Sequential	#DIV/0!	#DIV/0!
39	#DIV/0!	#DIV/0!	Global	#DIV/0!	#DIV/0!
40	#DIV/0!	#DIV/0!	Sequential	#DIV/0!	#DIV/0!
41	#DIV/0!	#DIV/0!	Sequential	#DIV/0!	#DIV/0!
42	8.070	Sequential	Sequential	0	3.930
43	#DIV/0!	#DIV/0!	Sequential	#DIV/0!	#DIV/0!
44	#DIV/0!	#DIV/0!	Global	#DIV/0!	#DIV/0!
45	10.523	Sequential	Sequential	0	6.523
46	#DIV/0!	#DIV/0!	Sequential	#DIV/0!	#DIV/0!
47	7.144	Sequential	Sequential	0	1.144
48	#DIV/0!	#DIV/0!	Global	#DIV/0!	#DIV/0!
49	12.212	Sequential	Sequential	0	0.212
50	#DIV/0!	#DIV/0!	Sequential	#DIV/0!	#DIV/0!
51	11.122	Sequential	Sequential	0	2.878
52	7.089	Sequential	Global	1	8.911
53	10.795	Sequential	Global	1	5.205
54	12.049	Sequential	Sequential	0	6.049
55	#DIV/0!	#DIV/0!	Sequential	#DIV/0!	#DIV/0!
56	11.340	Sequential	Sequential	0	3.340
57	9.869	Sequential	Sequential	0	0.131
58	9.869	Sequential	Sequential	0	0.131
59	#DIV/0!	#DIV/0!	Sequential	#DIV/0!	#DIV/0!
60	9.869	Sequential	Global	1	6.132
61	10.795	Sequential	Sequential	0	4.795
62	#DIV/0!	#DIV/0!	Sequential	#DIV/0!	#DIV/0!
63	8.288	Sequential	Sequential	0	0.288
64	9.869	Sequential	Global	1	6.132
65	8.888	Sequential	Sequential	0	1.113
66	#DIV/0!	#DIV/0!	Sequential	#DIV/0!	#DIV/0!
67	#DIV/0!	#DIV/0!	Global	#DIV/0!	#DIV/0!
68	8.070	Sequential	Sequential	0	4.070
69	#DIV/0!	#DIV/0!	Sequential	#DIV/0!	#DIV/0!
70	11.340	Sequential	Sequential	0	2.660
71	7.525	Sequential	Sequential	0	6.475
72	9.542	Sequential	Sequential	0	0.458
73	7.852	Sequential	Sequential	0	2.148
74	9.542	Sequential	Sequential	0	3.542
75	#DIV/0!	#DIV/0!	Sequential	#DIV/0!	#DIV/0!
			Group A Errors =	#DIV/0!	#DIV/0!
			Group A % Error =	#DIV/0!	#DIV/0!

Table 19: Group B results for predicting Sequential-Global learning style preferences

Participant	Predicted SG	Predicted Learning Style	Actual Learning Style	Error Count	Numerical Error
1	#DIV/0!	#DIV/0!	Sequential	#DIV/0!	#DIV/0!
2	#DIV/0!	#DIV/0!	Sequential	#DIV/0!	#DIV/0!
3	#DIV/0!	#DIV/0!	Sequential	#DIV/0!	#DIV/0!
4	#DIV/0!	#DIV/0!	Sequential	#DIV/0!	#DIV/0!
5	#DIV/0!	#DIV/0!	Sequential	#DIV/0!	#DIV/0!
6	#DIV/0!	#DIV/0!	Sequential	#DIV/0!	#DIV/0!
7	11.122	Sequential	Sequential	0	7.122
8	#DIV/0!	#DIV/0!	Sequential	#DIV/0!	#DIV/0!
9	#DIV/0!	#DIV/0!	Sequential	#DIV/0!	#DIV/0!
10	#DIV/0!	#DIV/0!	Global	#DIV/0!	#DIV/0!
11	#DIV/0!	#DIV/0!	Sequential	#DIV/0!	#DIV/0!
12	#DIV/0!	#DIV/0!	Sequential	#DIV/0!	#DIV/0!
13	#DIV/0!	#DIV/0!	Global	#DIV/0!	#DIV/0!
14	7.144	Sequential	Sequential	0	3.144
15	8.670	Sequential	Sequential	0	0.670
16	#DIV/0!	#DIV/0!	Global	#DIV/0!	#DIV/0!
17	#DIV/0!	#DIV/0!	Sequential	#DIV/0!	#DIV/0!
18	#DIV/0!	#DIV/0!	Global	#DIV/0!	#DIV/0!
19	#DIV/0!	#DIV/0!	Sequential	#DIV/0!	#DIV/0!
20	8.016	Sequential	Sequential	0	3.985
21	11.722	Sequential	Sequential	0	3.722
22	#DIV/0!	#DIV/0!	Sequential	#DIV/0!	#DIV/0!
23	#DIV/0!	#DIV/0!	Sequential	#DIV/0!	#DIV/0!
24	#DIV/0!	#DIV/0!	Sequential	#DIV/0!	#DIV/0!
25	11.994	Sequential	Sequential	0	2.006
			Group B Errors =	#DIV/0!	#DIV/0!
			Group B % Error =	#DIV/0!	#DIV/0!

Survey Response Analysis

The participants in Group B were asked to take a short course on how to solve Sudoku number puzzles (Instructables, 2006). The course was presented in a slide presentation format and afterwards the twenty-five participants were asked to answer the twelve questions shown in the media feedback survey in Appendix D. Each question in the survey related to a learning style preference dichotomy. Based on the predictive model, responses to the survey were also predicted.

Since no satisfactory prediction model for VV and SG were generated, the six (6) questions related to both VV and SG were eliminated from the analysis. Predicted responses were provided and compared to actual responses. The difference in actual and predicted responses determined the error rate calculated for each question and shown in Equation 3.

Equation 3: Response Error Calculation:

$$\sum |\text{Actual Response-Predicted Response}| / \text{Maximum Error}$$

The "Maximum Error" is equal to the total # of responses * (highest response possible – lowest response possible). In this case, there are twenty-five (25) responses for each question and the highest possible response is five (5) and the lowest possible response is one (1). Therefore "Maximum Error" for each question is one hundred (100). The "Response Error Calculation" is a percentage of the maximum possible error. The actual and predicted responses along with the "Response Error" calculation results are shown in Table 20. The total error across all six questions is 20.3%. This is consistent with the results from our predictive models for both AR and SI learning style preferences.

Table 20: Media feedback survey predicted and actual responses

	Survey Key:		Strongly Disagree = 1			Disagree = 2		Neutral = 3			Agree = 4		Strongly Agree = 5			Not Computed = NC		
	Question 1 Relates to SI			Question 2 Relates to SG			Question 3 Relates to AR			Question 4 Relates to VV			Question 5 Relates to SI			Question 6 Relates to AR		
Participant	Predicted	Actual	Difference	Predicted	Actual	Difference	Predicted	Actual	Difference	Predicted	Actual	Difference	Predicted	Actual	Difference	Predicted	Actual	Difference
1	2	1	1		5	NC	2	1	1		5	NC	2	1	1	4	2	2
2	3	1	2		4	NC	3	2	1		5	NC	3	2	1	3	2	1
3	2	2	0		4	NC	3	2	1		4	NC	2	2	0	3	1	2
4	2	1	1		4	NC	2	1	1		5	NC	2	2	0	4	1	3
5	2	1	1		5	NC	3	5	2		5	NC	2	2	0	3	1	2
6	2	1	1		4	NC	2	1	1		5	NC	2	3	1	4	1	3
7	3	2	1		4	NC	3	4	1		4	NC	3	1	2	3	3	0
8	2	1	1		4	NC	2	1	1		5	NC	2	1	1	4	2	2
9	3	1	2		4	NC	3	1	2		5	NC	3	4	1	3	1	2
10	3	2	1		4	NC	3	2	1		4	NC	3	2	1	3	1	2
11	3	1	2		5	NC	2	1	1		1	NC	3	2	1	4	2	2
12	2	2	0		4	NC	3	2	1		2	NC	2	2	0	3	1	2
13	3	3	0		2	NC	2	1	1		3	NC	3	4	1	4	4	0
14	2	4	2		4	NC	4	4	0		2	NC	2	2	0	2	3	1
15	2	2	0		4	NC	2	2	0		4	NC	2	2	0	4	4	0
16	3	3	0		3	NC	3	3	0		2	NC	3	2	1	3	3	0
17	3	3	0		4	NC	4	5	1		3	NC	3	3	0	2	2	0
18	2	2	0		3	NC	3	4	1		5	NC	2	1	1	3	2	1
19	2	2	0		2	NC	4	4	0		5	NC	2	2	0	2	2	0
20	2	1	1		2	NC	3	3	0		4	NC	2	2	0	3	3	0
21	3	3	0		4	NC	2	2	0		4	NC	3	3	0	4	5	1
22	3	2	1		4	NC	3	3	0		3	NC	3	2	1	3	4	1
23	2	2	0		3	NC	3	3	0		4	NC	2	2	0	3	3	0
24	2	2	0		2	NC	3	4	1		5	NC	2	1	1	3	3	0
25	3	3	0		3	NC	3	3	0		4	NC	3	3	0	3	4	1
		Error Rate:	17%		Error Rate:	NC		Error Rate:	18%		Error Rate:	NC		Error Rate:	14%		Error Rate:	28%

	Question 7 Relates to VV			Question 8 Relates to SG			Question 9 Relates to AR			Question 10 Relates to SG			Question 11 Relates to VV			Question 12 Relates to SI		
Participant	Predicted	Actual	Difference	Predicted	Actual	Difference	Predicted	Actual	Difference	Predicted	Actual	Difference	Predicted	Actual	Difference	Predicted	Actual	Difference
1		5	NC		3	NC	4	2	2		2	NC		2	NC	4	3	1
2		5	NC		2	NC	3	2	1		2	NC		4	NC	3	4	1
3		4	NC		1	NC	3	5	2		2	NC		2	NC	4	2	2
4		5	NC		2	NC	4	1	3		2	NC		2	NC	4	5	1
5		4	NC		2	NC	3	2	1		1	NC		2	NC	4	4	0
6		5	NC		2	NC	4	1	3		2	NC		3	NC	4	4	0
7		4	NC		1	NC	3	2	1		2	NC		2	NC	3	4	1
8		5	NC		1	NC	4	1	3		1	NC		3	NC	4	4	0
9		5	NC		1	NC	3	4	1		2	NC		4	NC	2	4	2
10		4	NC		2	NC	3	2	1		1	NC		2	NC	4	4	0
11		4	NC		4	NC	4	1	3		1	NC		1	NC	4	4	0
12		4	NC		1	NC	3	1	2		2	NC		3	NC	4	4	0
13		4	NC		4	NC	4	2	2		2	NC		2	NC	2	3	1
14		4	NC		2	NC	2	3	1		2	NC		2	NC	4	5	1
15		3	NC		4	NC	4	4	0		2	NC		4	NC	4	5	1
16		4	NC		3	NC	3	4	1		3	NC		3	NC	3	4	1
17		3	NC		2	NC	2	2	0		1	NC		2	NC	3	3	0
18		2	NC		3	NC	3	3	0		2	NC		2	NC	4	4	0
19		3	NC		4	NC	2	1	1		2	NC		1	NC	4	4	0
20		3	NC		2	NC	3	2	1		2	NC		2	NC	4	4	0
21		3	NC		2	NC	4	5	1		2	NC		1	NC	3	3	0
22		4	NC		2	NC	3	3	0		2	NC		2	NC	3	4	1
23		3	NC		3	NC	3	3	0		3	NC		4	NC	4	4	0
24		5	NC		4	NC	3	4	1		2	NC		2	NC	4	5	1
25		4	NC		5	NC	3	3	0		1	NC		2	NC	3	3	0
		Error Rate:	NC		Error Rate:	NC		Error Rate:	31%		Error Rate:	NC		Error Rate:	NC		Error Rate:	14%

The analysis of responses is shown in Table 21. The distribution of actual responses is consistent with percentage of participants expected to agree/disagree with media format of training scenario. The scenario provide was very active in content and the expectation was that people with active learning style preferences would agree that the format provided met their learning needs. The reflective learners on the other hand would tend to disagree. The same expectation held true for participants with sensing and intuitive learning style preferences.

Table 21: Response Analysis

<table>
<tr><th>Actual Responses</th><th>Frequency</th><th>Percentage</th><th>Percentage</th><th>Actual Percentage Active or Reflective</th><th>Actual Percentage Sensing or Intuitive</th></tr>
<tr><td>Strongly Disagree</td><td>34</td><td>22.67%</td><td rowspan="2">29.33% Disagree</td><td rowspan="2">24% Reflective</td><td rowspan="2">16% Intuitive</td></tr>
<tr><td>Disagree</td><td>46</td><td>30.67%</td></tr>
<tr><td>Neutral</td><td>30</td><td>20.00%</td><td rowspan="3">70.66% Agree or Neutral</td><td rowspan="3">76% Active</td><td rowspan="3">84% Sensing</td></tr>
<tr><td>Agree</td><td>31</td><td>20.67%</td></tr>
<tr><td>Strongly Agree</td><td>9</td><td>6.00%</td></tr>
<tr><td>Totals</td><td>150</td><td>100.00%</td><td colspan="3" rowspan="9">Distribution of actual responses are consistent with percentage expected to agree/disagree with media format of training scenario.

Scenario was heavily active in content and the expectation was that people with active learning style preferences would agree with the format and reflective learners would disagree. The same expectation held true for sensing and intuitive learners.</td></tr>
<tr><td></td><td></td><td></td></tr>
<tr><td>Predicted Responses</td><td>Frequency</td><td>Percentage</td></tr>
<tr><td>Strongly Disagree</td><td>0</td><td>0.00%</td></tr>
<tr><td>Disagree</td><td>44</td><td>29.33%</td></tr>
<tr><td>Neutral</td><td>71</td><td>47.33%</td></tr>
<tr><td>Agree</td><td>35</td><td>23.33%</td></tr>
<tr><td>Strongly Agree</td><td>0</td><td>0.00%</td></tr>
<tr><td>Totals</td><td>150</td><td>100.00%</td></tr>
</table>

Structural Equation Modeling

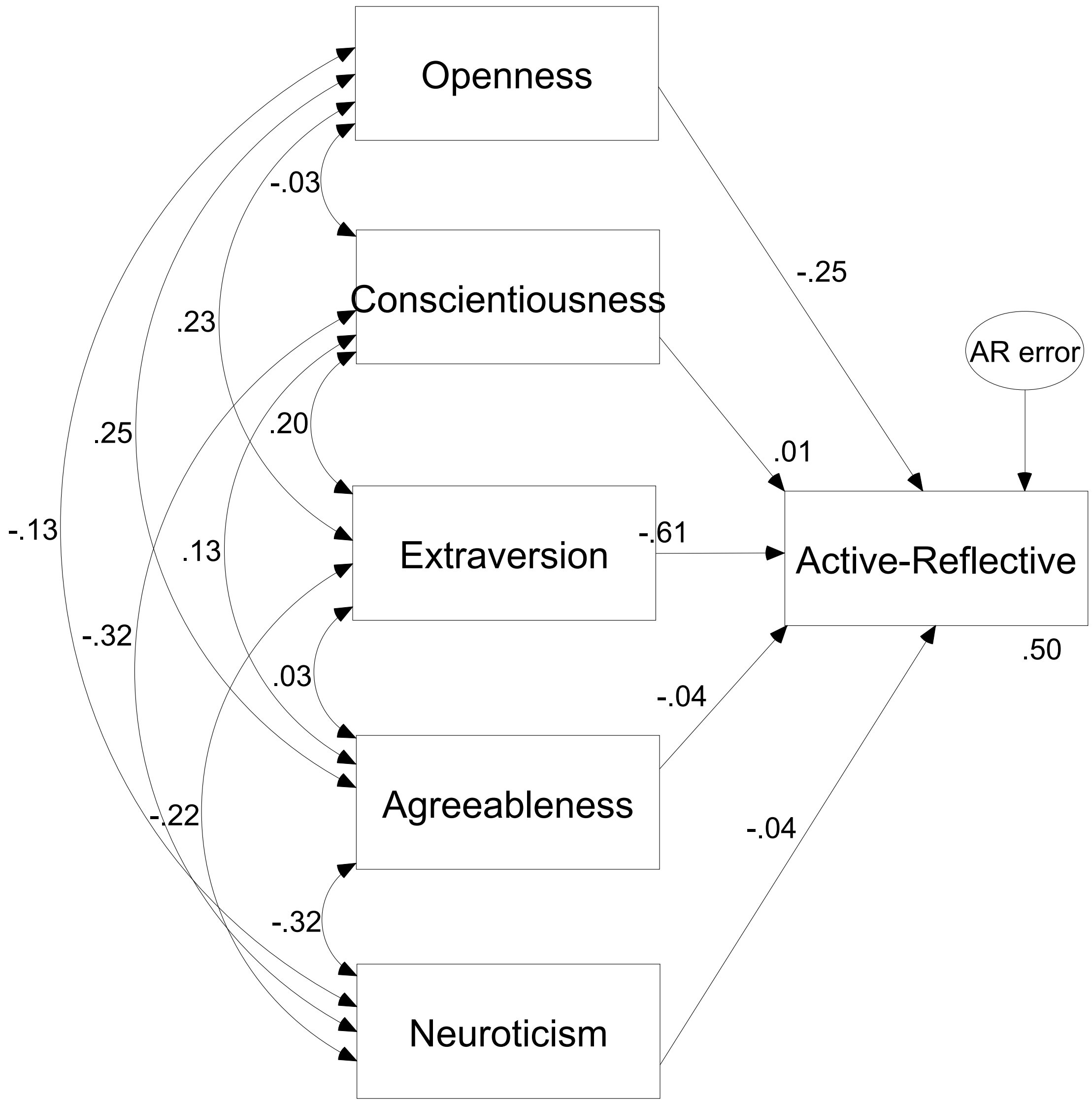

Figure 4: SEM Model for Active-Reflective (Group A - AMOS)

The model shown in Figure 4 was generated using the structural equation modeling tool, AMOS 5.0.1 (Build 5152). The advantage of using AMOS is that a multivariate analysis can be easily be conducted that evaluates the strength of the paths (or relationships). This is more comprehensive since AMOS examines all the interactions between variables. The diagram shows that the path (relationship) between extraversion and active-reflective has a correlation coefficient of -0.61 indicating an inverse relationship between these variables. This coefficient tells us that as extraversion goes up one standard deviation, active-reflective goes down by 0.61 standard deviations. A path is significant at the 95% confidence level when the absolute value of the critical ratio (C.R.) shown in Table 22 is > 1.96. Both extraversion and openness have significant relationships with active-reflective. This comparable to the regression analysis conducted earlier.

Table 22: Regression Weights: (Group A - AR model from AMOS)

	Estimate	S.E.	C.R.	P	Label
Active-Reflective <--- Openness	-.048	.016	-2.900	.004	par_1
Active-Reflective <--- Neuroticism	-.008	.013	-.626	.532	par_11
Active-Reflective <--- Agreeableness	-.008	.016	-.483	.629	par_12
Active-Reflective <--- Conscientiousness	.003	.015	.203	.839	par_13
Active-Reflective <--- Extraversion	-.115	.016	-7.153	***	par_14

The comparative fit index (CFI) for the Group AR structural equation model in Figure 4 is 1.000. CFI values can range from 0.1 and a CFI close to 1.000 indicates a good fit (Bentler, 1990). Fifty percent (50%) of the effect on AR was accounted for by the five factors in this model.

The model shown in Figure 5 shows the strongest path between a Five Factor Model variable and sensing-intuitive is the correlation of 0.47 between openness and SI. In Table 23, only the critical ratio for openness exceeds 1.96 and is therefore the only variable with a significant correlation at the 95% confidence level.

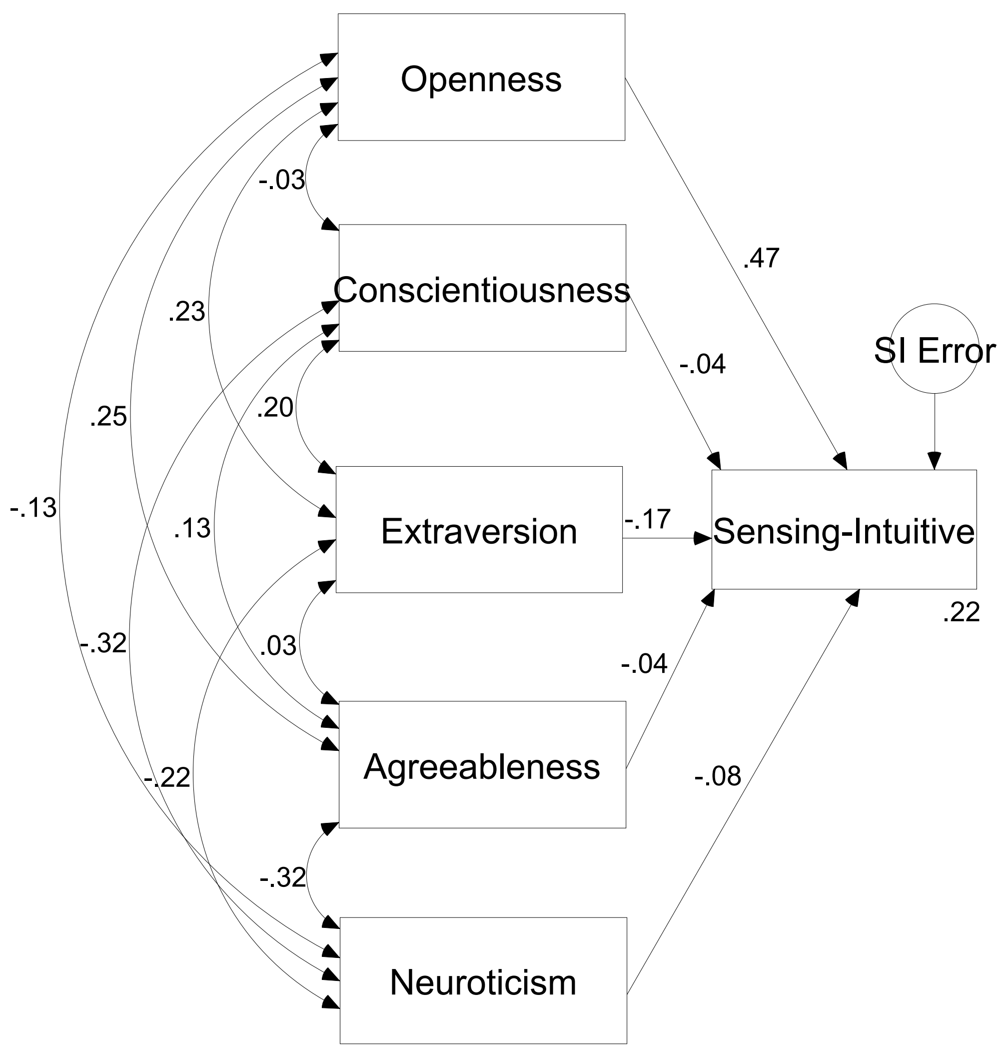

Figure 5: SEM Model for Sensing-Intuitive (Group A - AMOS)

The CFI for the SI model in Figure 5 is 1.000 indicating a good fit. Approximately 22% of the effect on SI was accounted for by the five factors in this model.

Table 23: Regression Weights: (Group A - SI model from AMOS)

	Estimate	S.E.	C.R.	P	Label
Sensing-Intuitive <--- Extraversion	-.034	.022	-1.562	.118	
Sensing-Intuitive <--- Agreeableness	-.008	.022	-.367	.714	
Sensing-Intuitive <--- Neuroticism	-.015	.018	-.871	.383	
Sensing-Intuitive <--- Conscientiousness	-.009	.021	-.440	.660	
Sensing-Intuitive <--- Openness	.097	.022	4.368	***	

CHAPTER FIVE: THESIS SUMMARY, RESEARCH CONCLUSIONS, LESSONS LEARNED AND SUGGESTED FUTURE RESEARCH

Chapter Five Summary

This chapter reviews the objectives of the thesis including motivations, processes, findings and conclusions. Limitations of the scope and testing methods are also discussed along with lessons learned and future research.

Thesis Summary

This thesis evaluated the relationship between personality preferences and learning style preferences in regard to ITS selection of media. "From the human-computer interaction point of view a careful examination is necessary of how to adapt the learning environment to the learner's goal and capability" (Oppermann, 1997). This thesis examined methods of predicting the media needs of learners that interact with ITS.

Thesis Limitations

Focusing on the direct effects of learning styles on media selection and personality preferences as predictors of learning style allowed this researcher to examine and experimentally establish learning style and personality preference relationships without the additional complexities of addressing student goals and knowledge gaps. This should be the goal of future research, but was not part of this research.

Conclusions

The null hypothesis that "there is no dependency between personality preference variables and learning style preference variables" was partly rejected based on the results of the correlation study of variables of the Big Five Personality Test and the Index of Learning Style for the sample population and measurement tools (Microsoft Excel data analysis package and AMOS) selected. Highly significant correlations between the personality preferences, openness and extraversion, were established for both the active-reflective and sensing-intuitive learning style preferences. Specifically, there is a dependent relationship between extraversion and the active-reflective scale and openness and the sensing-intuitive scale. The significance of these relationships is at $p \leq 0.01$. The sub null hypotheses for these cases are rejected in favor of the alternative hypothesis.

The sub null hypotheses for the following cases are rejected, but not in favor of the alternative hypothesis:

- relationship between sensing-intuiting learning preferences and extraversion
- relationship between visual-verbal learning preferences and extraversion
- relationship between visual-verbal learning preferences and openness
- relationship between sequential-global learning preferences and openness

The results were highly significant, but due to the limited number of significant results a viable predictive model could not be realized. The lack of a predictive model limits the ability to accept the alternative hypothesis.

The two models developed to predict learning style preferences had an error rate of ≤ 20%. This was far superior to guessing (50% error rate) or selecting one variable (i.e. active learning style) for every participant (30-49% error rate).

Lessons Learned

A more complex methodology could be undertaken with a larger participant pool. This would allow for refined subgroups while still maintaining the numbers needed for adequate statistical power. For example, subgroups in this study were male or high school graduate or age < 30. Larger sample populations would allow subgroup dyads or triads like male high school graduate age < 30 to be part of the study.

Future Research

A more expansive study should be undertaken to provide a larger validation group and additional refinement of the models developed in this thesis. Given additional time and resources, a more complex analysis could be pursued that includes methods to evaluate and predict student goals, knowledge gaps, motivation, values, trust and other variables critical to the learning process. The impact or effect size of implementing these strategies should be addressed in future research.

APPENDIX A: INSTITUTIONAL REVIEW BOARD (IRB) LETTER

University of Central Florida

Office of Research & Commercialization

August 25, 2006

Dear Mr. Sottilare:

The University of Central Florida's Institutional Review Board (IRB) received your protocol IRB #06-3718 entitled **"Modeling the influences of personality preferences on the selection of instructional strategies in intelligent tutoring systems."** The IRB Chair reviewed the study on 8/24/2006 and did not have any concerns with the proposed project. The Chair has indicated that under federal regulations (Category #4, research involving the collection or study of existing data, documents, pathological specimens or diagnostic specimens, if these sources are publicly available or if the information is recorded by the investigator in such a manner that subjects cannot be identified, directly or through identifiers linked to the subjects) this research is **exempt** from further review by our IRB, so an approval is not applicable and a renewal within one year is not required.

Please accept our best wishes for the success of your endeavors. Should you have any questions, please do not hesitate to call me at 407-823-2901.

Cordially,

Barbara Ward

Barbara Ward, CIM
UCF IRB Coordinator
(IRB00001138, FWA00000351, Exp. 5/13/07)

Copies: IRB File
Michael Proctor, Ph.D.
BW/jt

APPENDIX B: INDEX OF LEARNING STYLES (ILS) QUESTIONNAIRE AND LICENSE FOR USE

This appendix includes the ILS questionnaire, a license for use at educational institutions for educational purposes and an ILS sample report. In compliance with the license, a copyright is posted above.

Index of Learning Styles

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ILS Questionnaire Directions

For each of the 44 questions below, select either "a" or "b" to indicate your answer. Please choose only one answer for each question. If both "a" and "b" seem to apply to you, choose the one that applies more frequently.

1) I understand something better after I

   (a) try it out.

   (b) think it through.

2) I would rather be considered

   (a) realistic.

   (b) innovative.

3) When I think about what I did yesterday, I am most likely to get

   (a) a picture.

   (b) words.

4) I tend to

   (a) understand details of a subject but may be fuzzy about its overall structure.

   (b) understand the overall structure but may be fuzzy about details.

5) When I am learning something new, it helps me to

   (a) talk about it.

   (b) think about it.

6) If I were a teacher, I would rather teach a course

   (a) that deals with facts and real life situations.

   (b) that deals with ideas and theories.

7) I prefer to get new information in

   (a) pictures, diagrams, graphs, or maps.

   (b) written directions or verbal information.

8) Once I understand

   (a) all the parts, I understand the whole thing.

   (b) the whole thing, I see how the parts fit.

9) In a study group working on difficult material, I am more likely to

   (a) jump in and contribute ideas.

   (b) sit back and listen.

10) I find it easier

   (a) to learn facts.

   (b) to learn concepts.

11) In a book with lots of pictures and charts, I am likely to

   (a) look over the pictures and charts carefully.

   (b) focus on the written text.

12) When I solve math problems

   (a) I usually work my way to the solutions one step at a time.

   (b) I often just see the solutions but then have to struggle to figure out the steps to get to them.

13) In classes I have taken

   (a) I have usually gotten to know many of the students.

   (b) I have rarely gotten to know many of the students.

14) In reading nonfiction, I prefer

(a) something that teaches me new facts or tells me how to do something.

(b) something that gives me new ideas to think about.

15) I like teachers

(a) who put a lot of diagrams on the board.

(b) who spend a lot of time explaining.

16) When I'm analyzing a story or a novel

(a) I think of the incidents and try to put them together to figure out the themes.

(b) I just know what the themes are when I finish reading and then I have to go back and find the incidents that demonstrate them.

17) When I start a homework problem, I am more likely to

(a) start working on the solution immediately.

(b) try to fully understand the problem first.

18) I prefer the idea of

(a) certainty.

(b) theory.

19) I remember best

(a) what I see.

(b) what I hear.

20) It is more important to me that an instructor

(a) lay out the material in clear sequential steps.

(b) give me an overall picture and relate the material to other subjects.

21) I prefer to study

(a) in a study group.

(b) alone.

22) I am more likely to be considered

(a) careful about the details of my work.

(b) creative about how to do my work.

23) When I get directions to a new place, I prefer

(a) a map.

(b) written instructions.

24) I learn

(a) at a fairly regular pace. If I study hard, I'll "get it."

(b) in fits and starts. I'll be totally confused and then suddenly it all "clicks."

25) I would rather first

(a) try things out.

(b) think about how I'm going to do it.

26) When I am reading for enjoyment, I like writers to

(a) clearly say what they mean.

(b) say things in creative, interesting ways.

27) When I see a diagram or sketch in class, I am most likely to remember

(a) the picture.

(b) what the instructor said about it.

28) When considering a body of information, I am more likely to

   (a) focus on details and miss the big picture.

   (b) try to understand the big picture before getting into the details.

29) I more easily remember

   (a) something I have done.

   (b) something I have thought a lot about.

30) When I have to perform a task, I prefer to

   (a) master one way of doing it.

   (b) come up with new ways of doing it.

31) When someone is showing me data, I prefer

   (a) charts or graphs.

   (b) text summarizing the results.

32) When writing a paper, I am more likely to

   (a) work on (think about or write) the beginning of the paper and progress forward.

   (b) work on (think about or write) different parts of the paper and then order them.

33) When I have to work on a group project, I first want to

   (a) have "group brainstorming" where everyone contributes ideas.

   (b) brainstorm individually and then come together as a group to compare ideas.

34) I consider it higher praise to call someone

(a) sensible.

(b) imaginative.

35) When I meet people at a party, I am more likely to remember

(a) what they looked like.

(b) what they said about themselves.

36) When I am learning a new subject, I prefer to

(a) stay focused on that subject, learning as much about it as I can.

(b) try to make connections between that subject and related subjects.

37) I am more likely to be considered

(a) outgoing.

(b) reserved.

38) I prefer courses that emphasize

(a) concrete material (facts, data).

(b) abstract material (concepts, theories).

39) For entertainment, I would rather

(a) watch television.

(b) read a book.

40) Some teachers start their lectures with an outline of what they will cover. Such outlines are

(a) somewhat helpful to me.

(b) very helpful to me.

41) The idea of doing homework in groups, with one grade for the entire group,

(a) appeals to me.

(b) does not appeal to me.

42) When I am doing long calculations,

(a) I tend to repeat all my steps and check my work carefully.

(b) I find checking my work tiresome and have to force myself to do it.

43) I tend to picture places I have been

(a) easily and fairly accurately.

(b) with difficulty and without much detail.

44) When solving problems in a group, I would be more likely to

(a) think of the steps in the solution process.

(b) think of possible consequences or applications of the solution in a wide range of areas.

A sample report for the ILS is shown in Figure 6 below.

NC STATE UNIVERSITY

Learning Styles Results

```
Results for: SAMPLE

ACT                X                                           REF
       11   9   7   5   3   1   1   3   5   7   9   11
                           <-- -->

SEN                        X                                   INT
       11   9   7   5   3   1   1   3   5   7   9   11
                           <-- -->

VIS                                    X                       VRB
       11   9   7   5   3   1   1   3   5   7   9   11
                           <-- -->

SEQ                    X                                       GLO
       11   9   7   5   3   1   1   3   5   7   9   11
                           <-- -->
```

Figure 6: Sample Learning Style Results from ILS

APPENDIX C: TRAINING SCENARIO FOR THE EXPERIMENTATION PROCESS

In lieu of creating a large number of scenarios to match every conceivable learning style preference combination, the experiment for this thesis will provide a single scenario that is purposely biased to provide:

- high active content: action-focused, learn-by-doing activities like making selections and completing activities using mouse action vice reflective activities like keeping a journal
- high sequential content: media includes structured, orderly and linear information like steps in a process vice random and holistic data
- high sensing content: media includes concrete facts and observed data vice theories or models
- high visual content: media includes movies, graphs, charts, text or symbols vice verbal stimulation.

Based on these learning style preferences, a training aid for learning how to solve "sudoku" number puzzles will be used as the training scenario for this experiment. The primary basis for designing this training scenario is the "Solve Sudoku (Without even thinking!)" webpage (Instructables, 2006). It is highly sequential and focused on data (numbers and grid positions). The information provided in the instructions is very factual and applied to solving a specific problem. The instructions are highly visual and provide good active content. Some additional interaction will be added to increase the active content.

APPENDIX D: MEDIA FEEDBACK SURVEY

Questions for the media feedback survey were based on the eight factors in the ILS factor analysis and responses are on the 5 point - Likert scale. For each media feedback survey, questions were provided in rotating order so there were no ordering effects or bias.

1. The information presented was too abstract. [relates to SI scale]

   Strongly Disagree Disagree Neutral Agree Strongly Agree

2. The information provided had the right amount of detail. [Sequential-Global scale]

   Strongly Disagree Disagree Neutral Agree Strongly Agree

3. There was not enough time to complete the task [relates to Active-Reflective scale]

   Strongly Disagree Disagree Neutral Agree Strongly Agree

4. It was easy to remember the text presented. [relates to Visual-Verbal scale]

   Strongly Disagree Disagree Neutral Agree Strongly Agree

5. The task was too structured. [relates to SI scale]

   Strongly Disagree Disagree Neutral Agree Strongly Agree

6. The task would have been more interesting if I worked in a group. [relates to AR scale]

   Strongly Disagree Disagree Neutral Agree Strongly Agree

7. It was easy to remember the pictures presented. [Visual Verbal scale]

   Strongly Disagree Disagree Neutral Agree Strongly Agree

8. The course jumped into the process too quickly without explaining the concept first. [relates to Sequential-Global scale]

   Strongly Disagree Disagree Neutral Agree Strongly Agree

9. It took too long to get started with the task. [Active-Reflective scale]

   Strongly Disagree Disagree Neutral Agree Strongly Agree

10. The presentation seemed disjointed. [Sequential-Global scale]

Strongly Disagree Disagree Neutral Agree Strongly Agree

11. There was too much text in the presentation. [Visual Verbal scale]

Strongly Disagree Disagree Neutral Agree Strongly Agree

12. I enjoyed the material presented in this course. [relates to SI scale]

Strongly Disagree Disagree Neutral Agree Strongly Agree

APPENDIX E: DEMOGRAPHICS SURVEY

1. Your age is: ____________.

2. Your are: (circle one)

    a. male
    b. female

3. The highest level of education you have completed is: (circle one)

    a. Less than 12 years
    b. High School
    c. Bachelors Degree
    d. Masters Degree
    e. Doctoral Degree

4. If you are a University of Central Florida student, which college do you attend? (circle one)

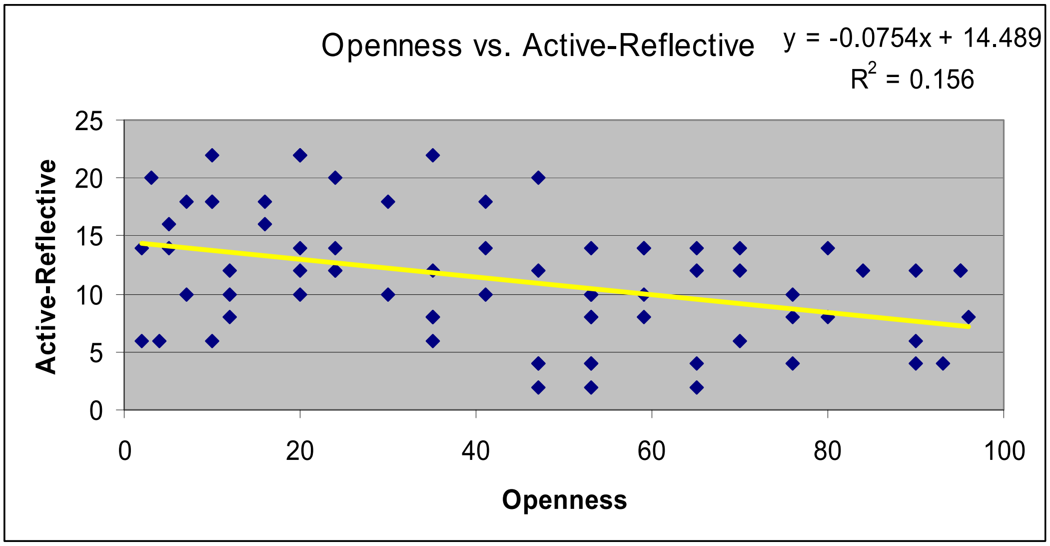
    a. Arts & Humanities
    b. Biomedical Sciences
    c. Burnett Honors College
    d. Business Administration
    e. Education
    f. Engineering & Computer Science
    g. Health & Public Affairs
    h. Hospitality Management
    i. Optics & Photonics
    j. Sciences
    k. Other ________________________
    l. Not Applicable

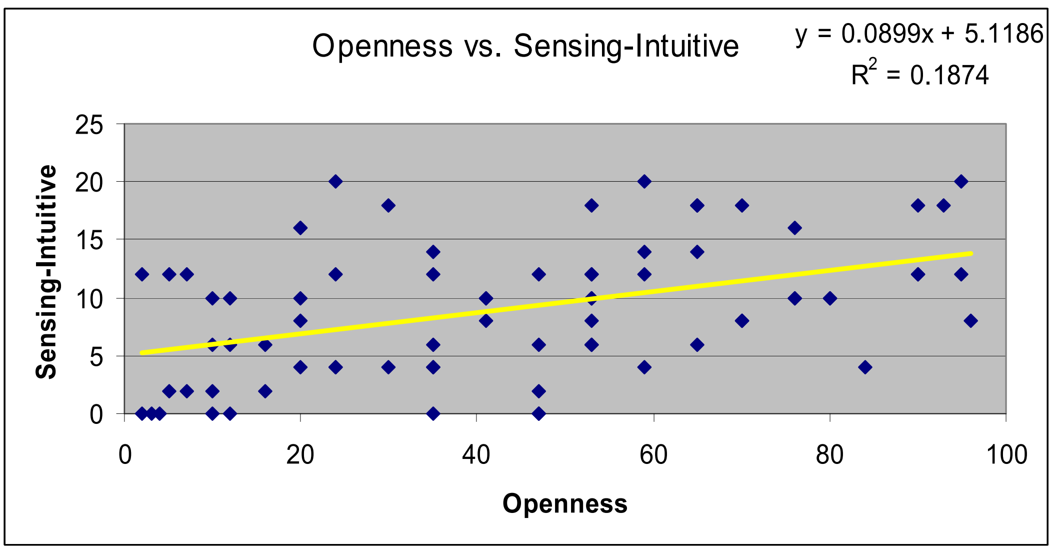
5. If you are working fulltime, what is your occupation? (circle one)

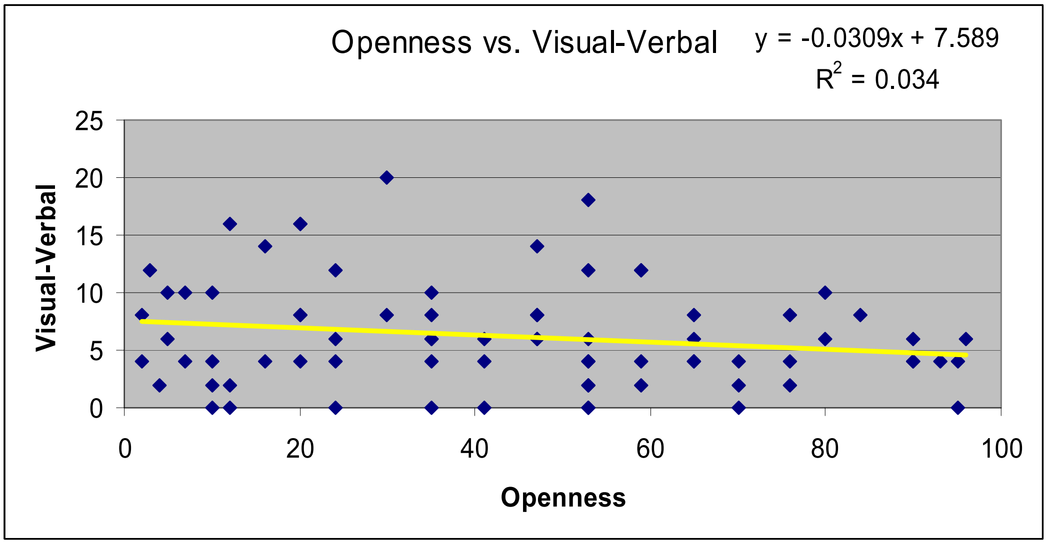
   a. Management, business and financial operations
   b. Professional (engineers and scientists)
   c. Professional (legal)
   d. Professional (health)
   e. Professional (education)
   f. Service or Sales
   g. Administrative
   h. Farming
   i. Construction
   j. Installation
   k. Production (fabricators, manufacturers, processors)
   l. Transportation
   m. Armed Forces
   n. Not applicable

APPENDIX F: SCATTER DIAGRAMS WITH LINEAR TRENDLINES

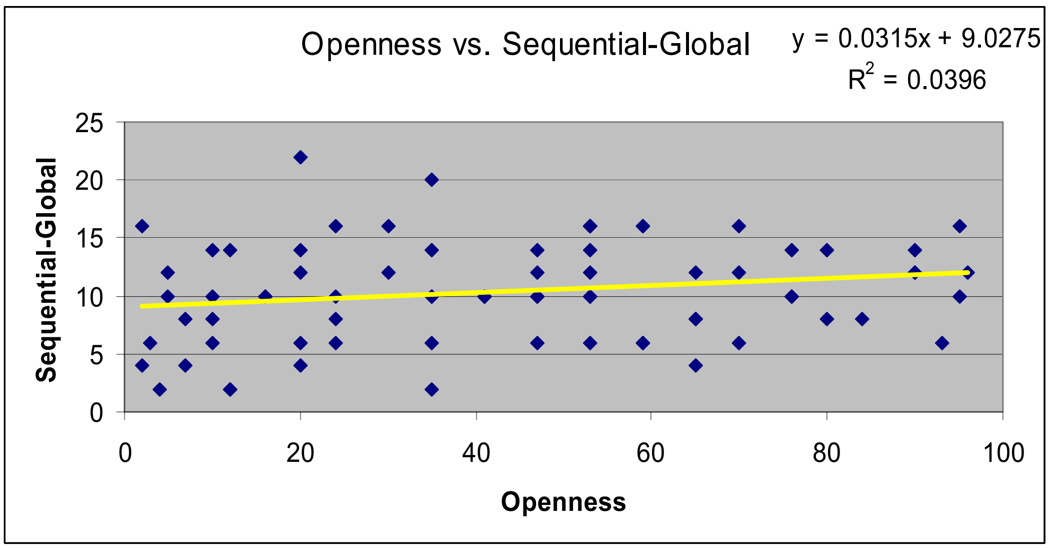
This appendix contains the scatter diagrams and associated trend lines for the points plotted for each independent-dependent variable pair for the Group A data collected. The regression equations are noted on each diagram along with the correlation coefficient.



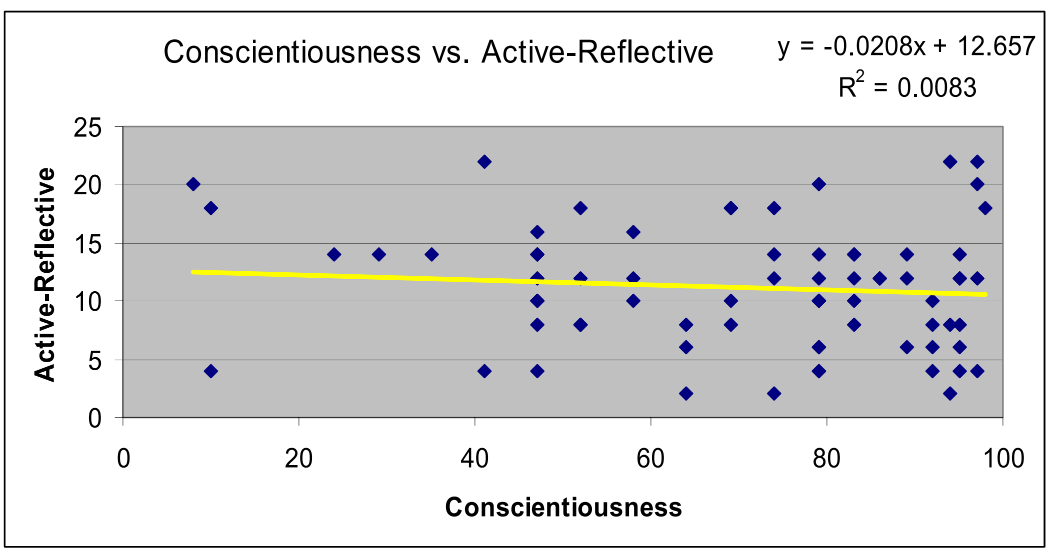




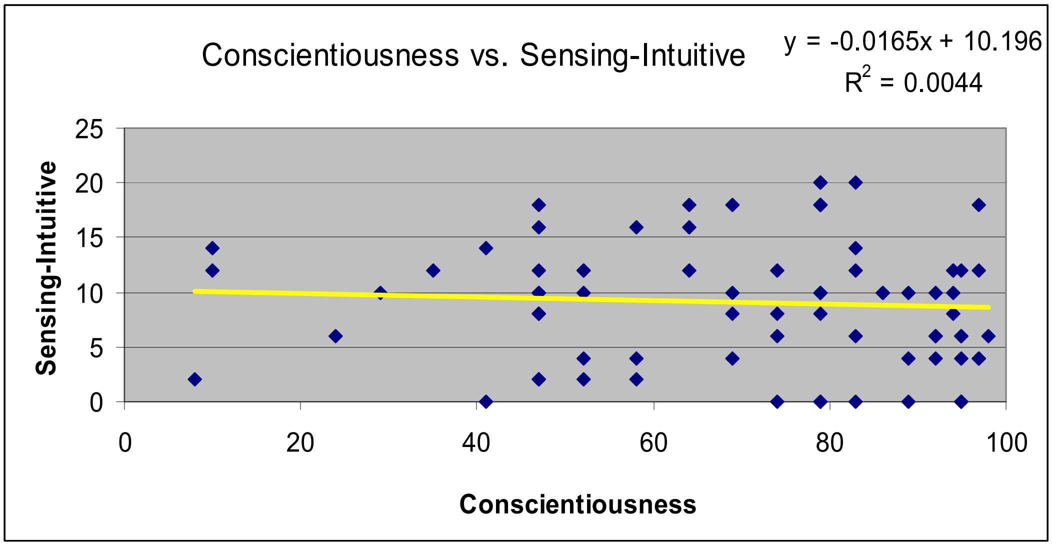
Openness vs. Visual-Verbal
y = -0.0309x + 7.589
R2 = 0.034
Visual-Verbal
Openness



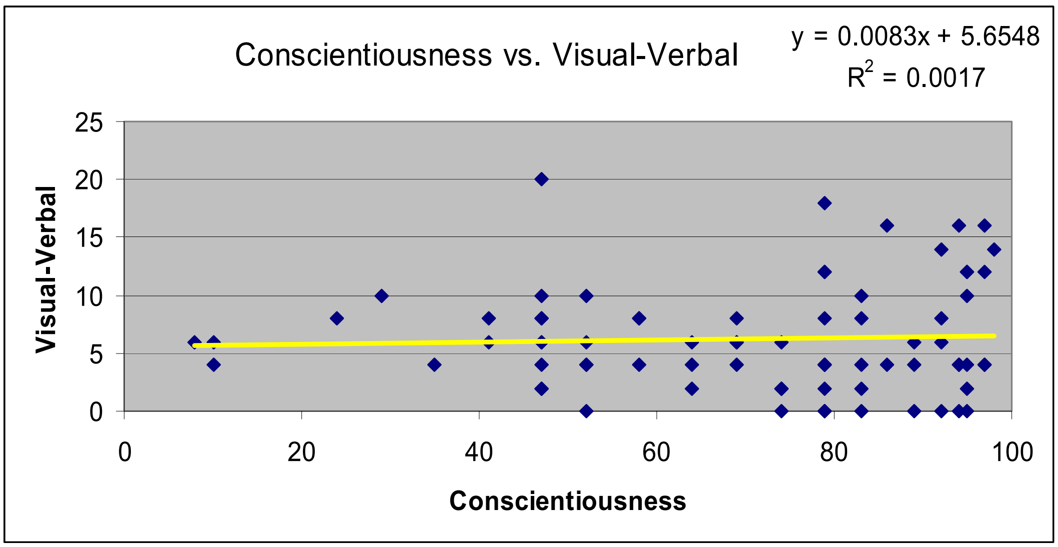
Openness vs. Sequential-Global
y = 0.0315x + 9.0275
R2 = 0.0396
Sequential-Global
Openness



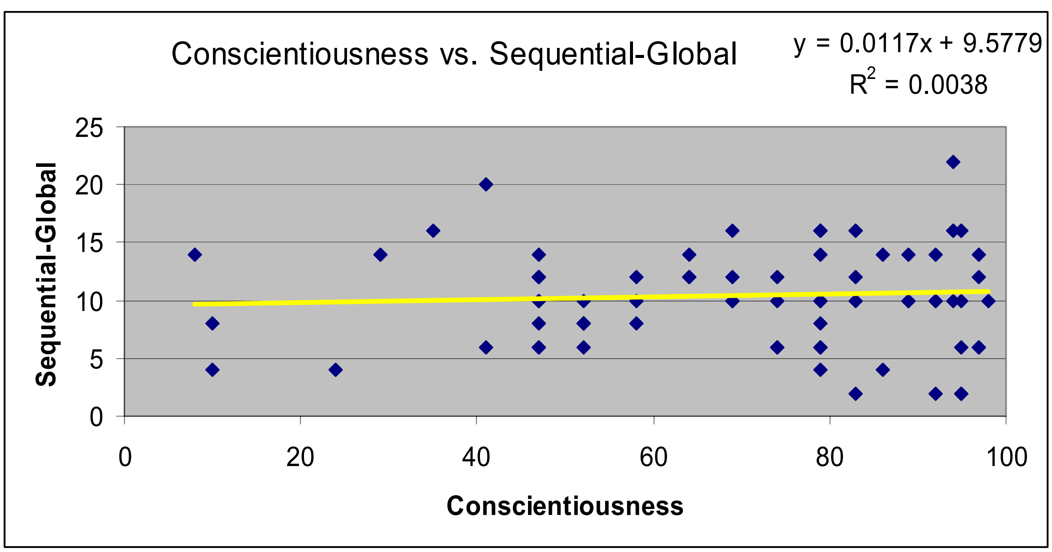
Conscientiousness vs. Active-Reflective
y = -0.0208x + 12.657
R2 = 0.0083
Active-Reflective
Conscientiousness



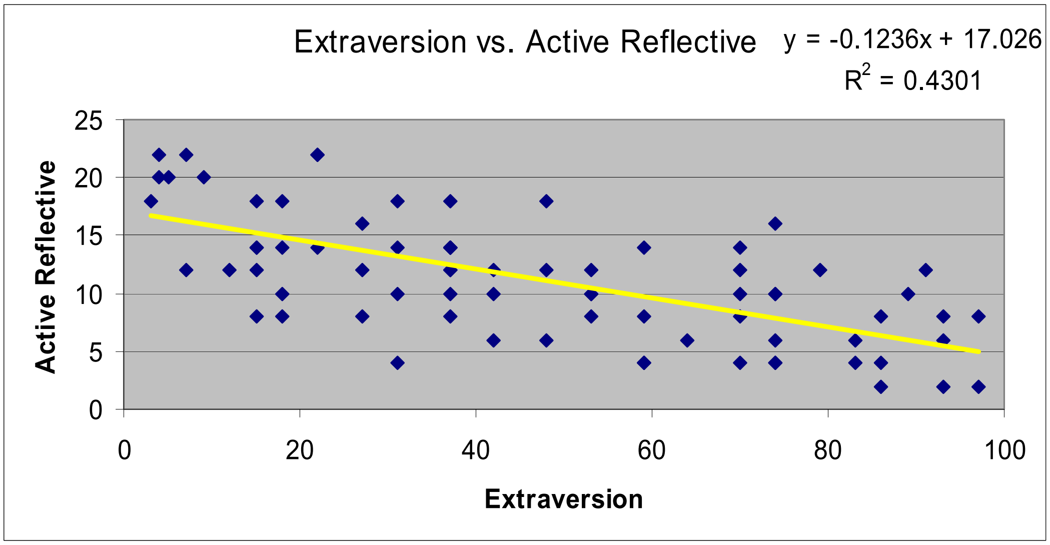
Conscientiousness vs. Sensing-Intuitive
y = -0.0165x + 10.196
R^2 = 0.0044
Sensing-Intuitive
25
20
15
10
5
0
0
20
40
60
80
100
Conscientiousness

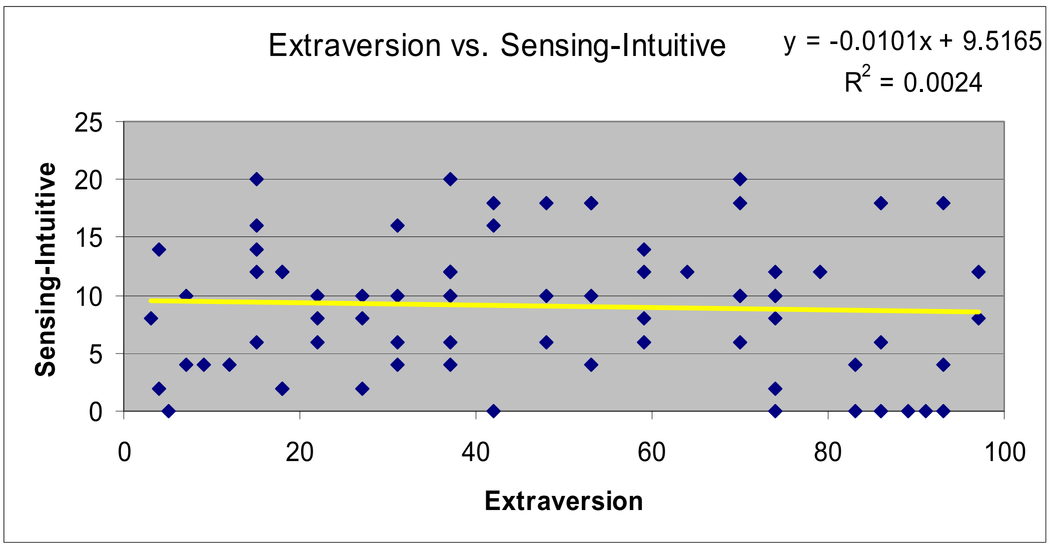


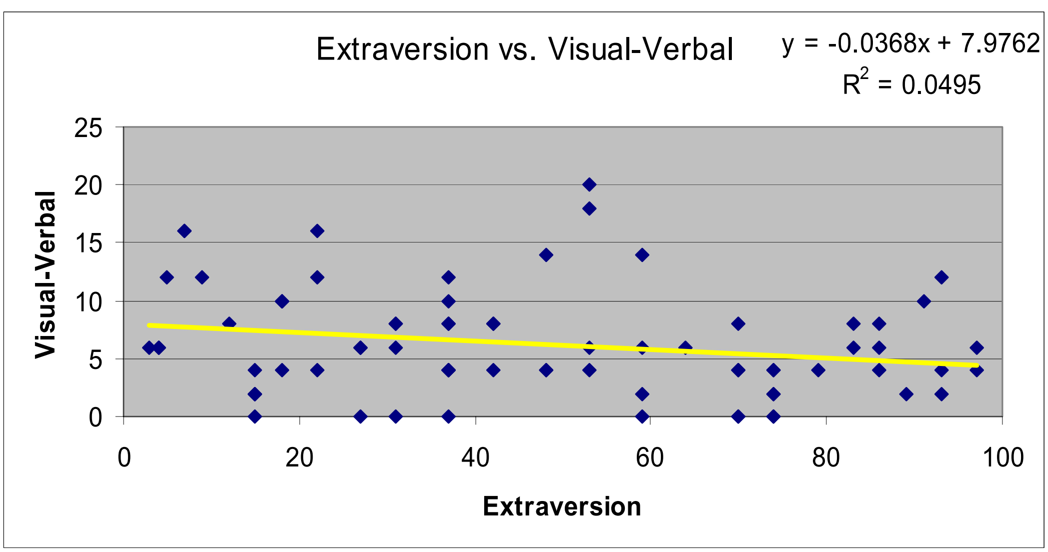
Conscientiousness vs. Visual-Verbal
y = 0.0083x + 5.6548
R^2 = 0.0017
Visual-Verbal
25
20
15
10
5
0
0
20
40
60
80
100
Conscientiousness

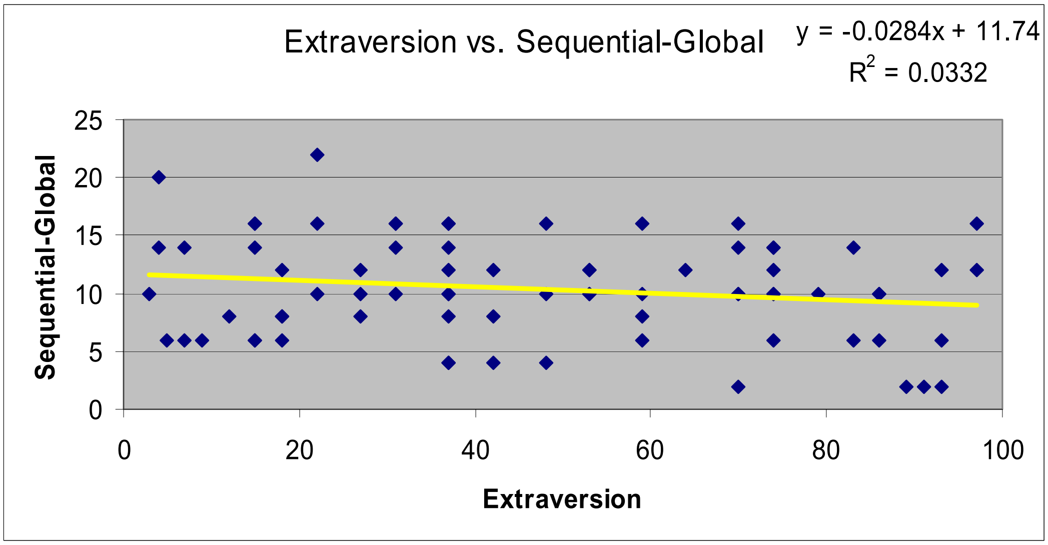


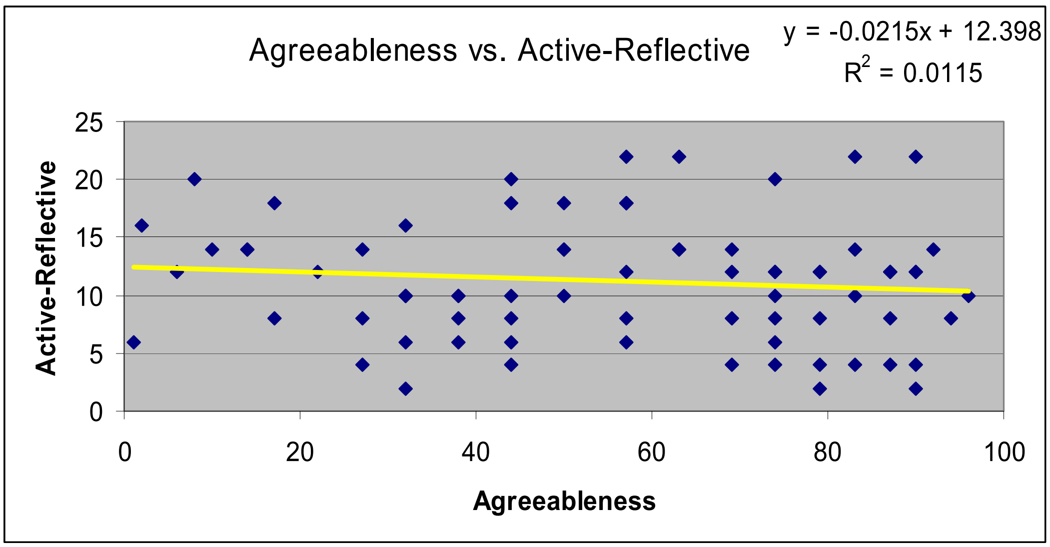
Conscientiousness vs. Sequential-Global
y = 0.0117x + 9.5779
R^2 = 0.0038
Sequential-Global
25
20
15
10
5
0
0
20
40
60
80
100
Conscientiousness

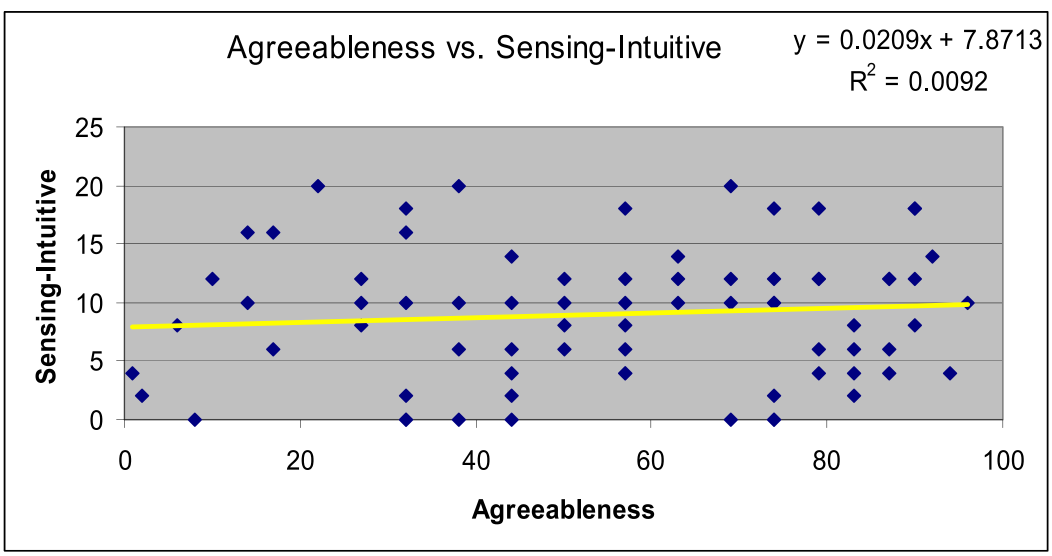

Extraversion vs. Active Reflective
y = -0.1236x + 17.026
R2 = 0.4301
Active Reflective
Extraversion
0
5
10
15
20
25
0
20
40
60
80
100

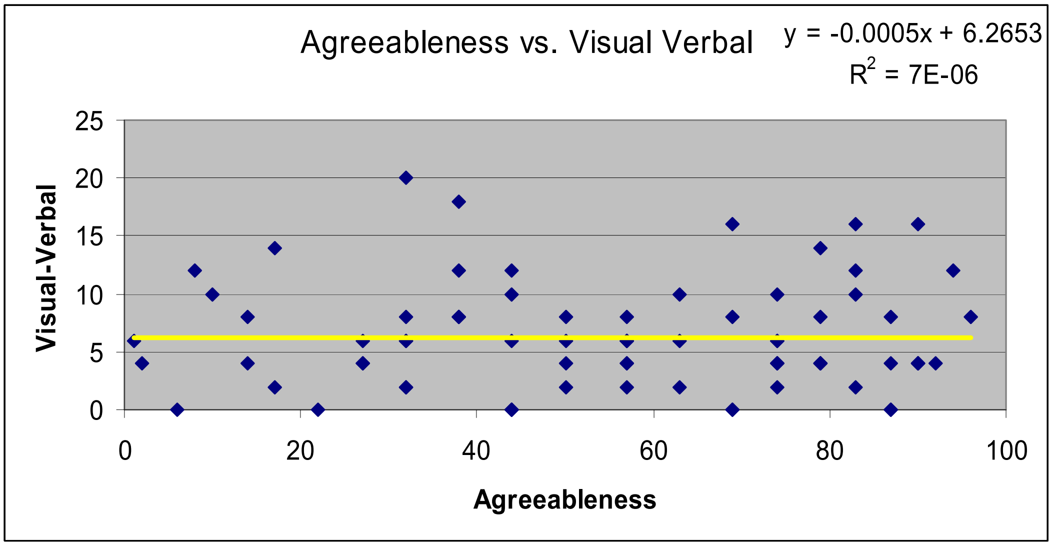

Extraversion vs. Sensing-Intuitive
y = -0.0101x + 9.5165
R2 = 0.0024
Sensing-Intuitive
Extraversion
0
5
10
15
20
25
0
20
40
60
80
100

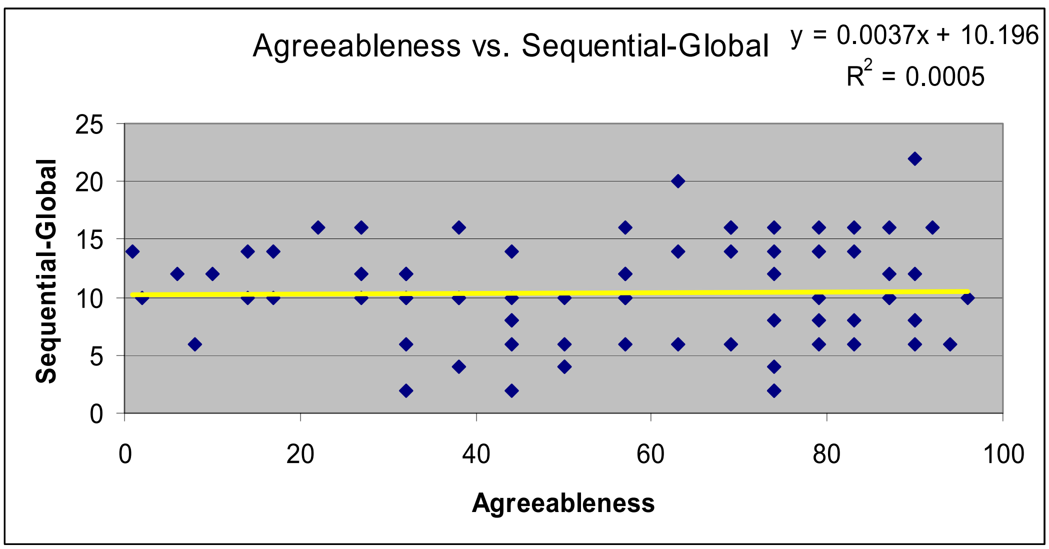

Extraversion vs. Visual-Verbal
y = -0.0368x + 7.9762
R2 = 0.0495
Visual-Verbal
Extraversion
0
5
10
15
20
25
0
20
40
60
80
100

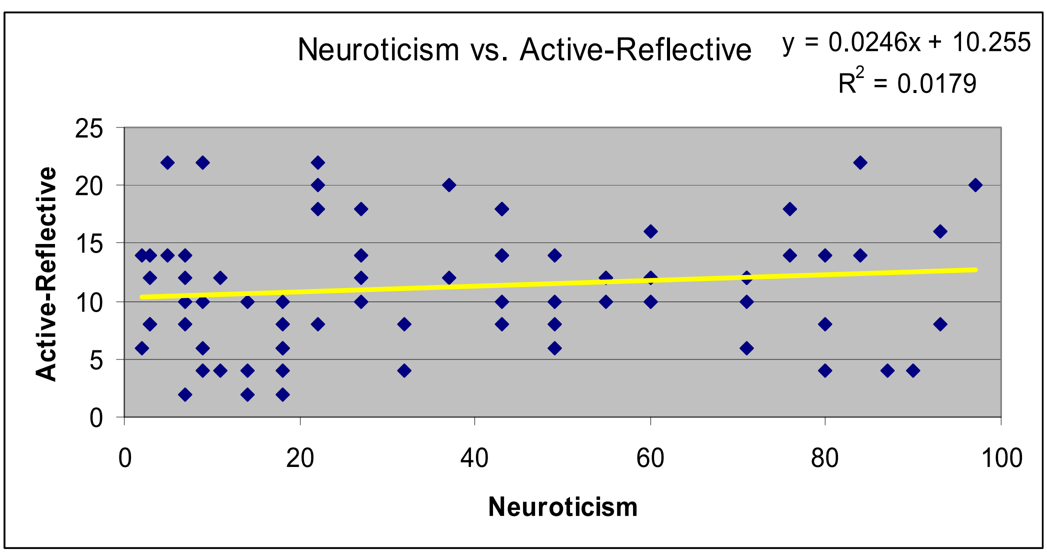

Extraversion vs. Sequential-Global
y = -0.0284x + 11.74
R2 = 0.0332
Sequential-Global
Extraversion
0
5
10
15
20
25
0
20
40
60
80
100

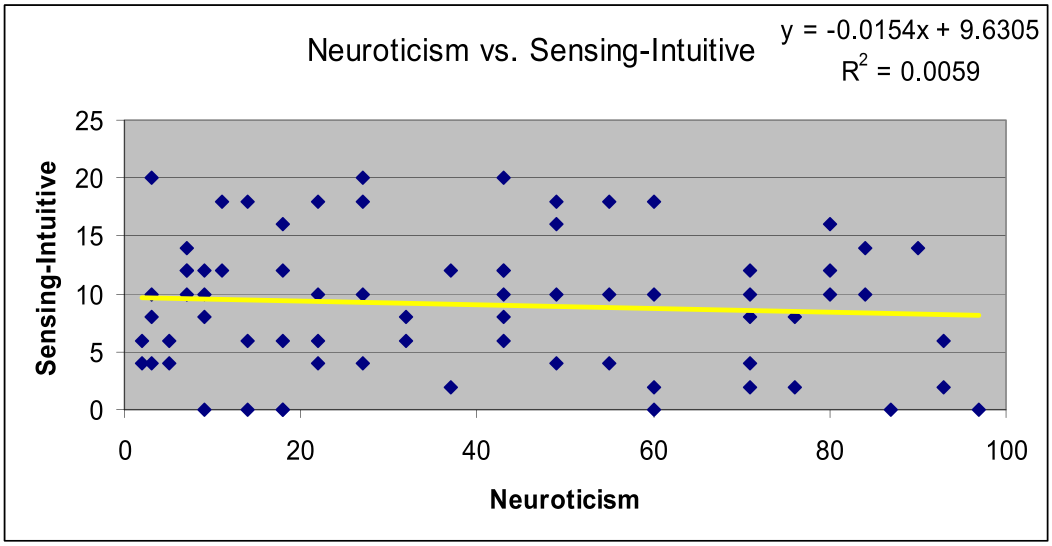

Agreeableness vs. Active-Reflective
y = -0.0215x + 12.398
R2 = 0.0115
Active-Reflective
Agreeableness
0
5
10
15
20
25
0
20
40
60
80
100

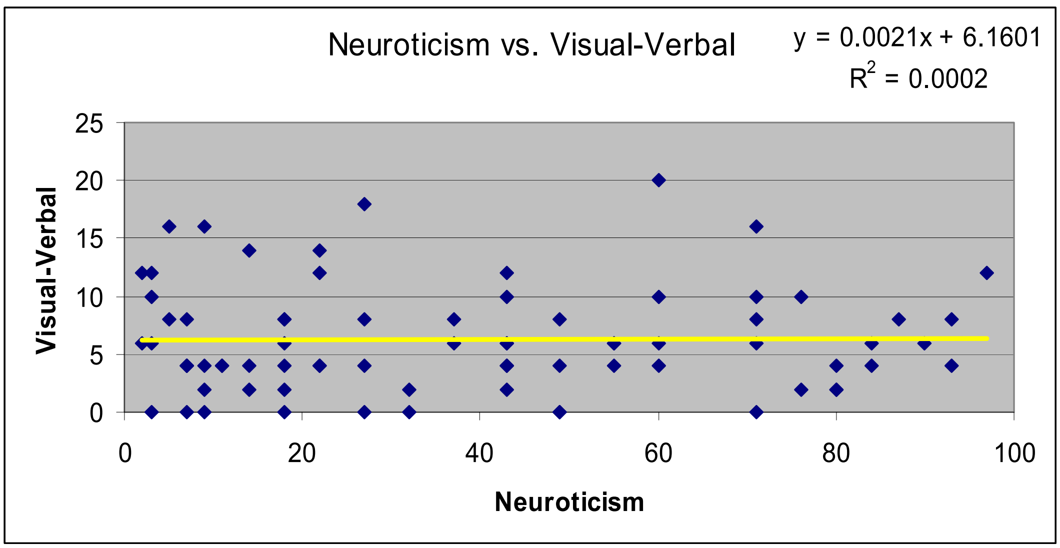

Agreeableness vs. Sensing-Intuitive
y = 0.0209x + 7.8713
R2 = 0.0092
Sensing-Intuitive
Agreeableness
0
5
10
15
20
25
0
20
40
60
80
100

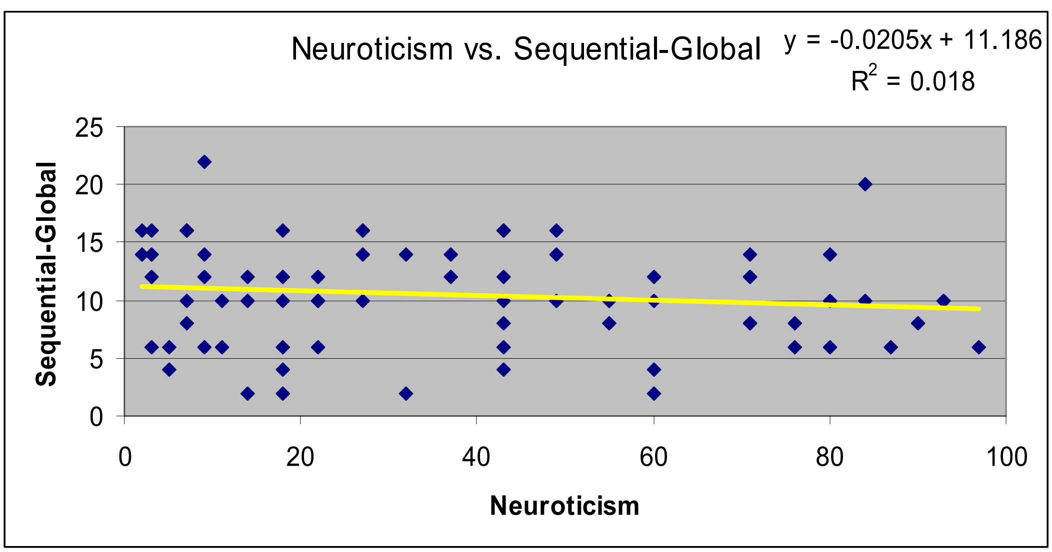

Agreeableness vs. Visual Verbal
y = -0.0005x + 6.2653
R2 = 7E-06
Visual-Verbal
Agreeableness
0
5
10
15
20
25
0
20
40
60
80
100


Agreeableness vs. Sequential-Global
y = 0.0037x + 10.196
R2 = 0.0005
Sequential-Global
Agreeableness
0
5
10
15
20
25
0
20
40
60
80
100


Neuroticism vs. Active-Reflective
y = 0.0246x + 10.255
R2 = 0.0179
Active-Reflective
Neuroticism
0
5
10
15
20
25
0
20
40
60
80
100


Neuroticism vs. Sensing-Intuitive
y = -0.0154x + 9.6305
R^2 = 0.0059
Sensing-Intuitive
0
5
10
15
20
25
0
20
40
60
80
100
Neuroticism


Neuroticism vs. Visual-Verbal
y = 0.0021x + 6.1601
R^2 = 0.0002
Visual-Verbal
0
5
10
15
20
25
0
20
40
60
80
100
Neuroticism


Neuroticism vs. Sequential-Global
y = -0.0205x + 11.186
R^2 = 0.018
Sequential-Global
0
5
10
15
20
25
0
20
40
60
80
100
Neuroticism

APPENDIX G: REGRESSION ANALYSIS AND SIGNIFICANCE TESTING RESULTS

SUMMARY OUTPUT FOR ALL of GROUP A where AR is predicted by E						
Regression Statistics						
Multiple R	0.655839398	Correlation between AR and E is significant at p = 0.001				
R Square	0.430125316					
Adjusted R Square	0.422318813					
Standard Error	4.014052965					
Observations	75					
ANOVA						
	df	*SS*	*MS*	*F*	*Significance F*	
Regression	1	887.7786519	887.7787	55.09834	1.70048E-10	
Residual	73	1176.221348	16.11262			
Total	74	2064				
	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*
Intercept	17.02555287	0.911466535	18.6793	1.58E-29	15.20900146	18.84210429
Extraversion	-0.123632277	0.01665569	-7.42283	1.7E-10	-0.15682704	-0.090437513

SUMMARY OUTPUT FOR ALL of GROUP A where SI is predicted by O						
Regression Statistics						
Multiple R	0.432839549	Correlation between SI and O is significant at p = 0.001				
R Square	0.187350075					
Adjusted R Square	0.176217885					
Standard Error	5.214844785					
Observations	75					
ANOVA						
	df	*SS*	*MS*	*F*	*Significance F*	
Regression	1	457.6737523	457.6738	16.82958	0.00010511	
Residual	73	1985.206248	27.19461			
Total	74	2442.88				
	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*
Intercept	5.118575543	1.129742259	4.530746	2.25E-05	2.86700094	7.370150145
Openness	0.089913431	0.021917346	4.102387	0.000105	0.046232195	0.133594668

SUMMARY OUTPUT FOR ALL of GROUP A where VV is predicted by E						
Regression Statistics						
Multiple R	0.222586018	Correlation between VV and E is NOT significant at p = 0.05				
R Square	0.049544536					
Adjusted R Square	0.036524598					
Standard Error	4.552315313					
Observations	75					
ANOVA						
	df	*SS*	*MS*	*F*	*Significance F*	
Regression	1	78.85904642	78.85905	3.80528203	0.054930041	
Residual	73	1512.820954	20.72357			
Total	74	1591.68				
	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*
Intercept	7.97624321	1.033689167	7.716288	4.79965E-11	5.916102274	10.03638415
Extraversion	-0.036847267	0.018889126	-1.95071	0.054930041	-0.074493265	0.000798732

SUMMARY OUTPUT FOR ALL of GROUP A where SG is predicted by O						
Regression Statistics						
Multiple R	0.198987203	Correlation between SG and O is NOT significant at p = 0.05				
R Square	0.039595907					
Adjusted R Square	0.026439686					
Standard Error	4.316156643					
Observations	75					
ANOVA						
	df	*SS*	*MS*	*F*	*Significance F*	
Regression	1	56.06780402	56.0678	3.009671883	0.08698944	
Residual	73	1359.932196	18.62921			
Total	74	1416				
	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*
Intercept	9.027467543	0.935050756	9.654521	1.11502E-14	7.163912811	10.89102227
Openness	0.031470478	0.018140271	1.734841	0.08698944	-0.004683054	0.06762401

SUMMARY OUTPUT FOR Subgroup Age <30 where AR is predicted by E						
Regression Statistics						
Multiple R	0.609973215	Correlation between AR and E is significant at p = 0.001 for Subgroup Age <30				
R Square	0.372067323					
Adjusted R Square	0.353039061					
Standard Error	3.812534356					
Observations	35					
ANOVA						
	df	*SS*	*MS*	*F*	*Significance F*	
Regression	1	284.2169131	284.2169131	19.55340458	0.000100156	
Residual	33	479.6688011	14.53541822			
Total	34	763.8857143				
	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*
Intercept	17.01797218	1.238181248	13.74433041	3.28007E-15	14.49887149	19.53707287
Extraversion	-0.109670929	0.024801636	-4.421923177	0.000100156	-0.160130277	-0.059211581

SUMMARY OUTPUT FOR Subgroup Age <30 where SI is predicted by E							
Regression Statistics							
Multiple R	0.341481474	Correlation between SI and E is NOT significant at p = 0.05 for Subgroup Age <30					
R Square	0.116609597						
Adjusted R Square	0.089840191						
Standard Error	3.963947095						
Observations	35						
ANOVA							
	df	*SS*	*MS*	*F*	*Significance F*		
Regression	1	68.4465016	68.4465016	4.356077086	0.044678652		
Residual	33	518.524927	15.71287657				
Total	34	586.9714286					
	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lc*
Intercept	10.46569035	1.287354947	8.12960744	2.19933E-09	7.846544943	13.08483576	7
Extraversion	-0.053819814	0.02578662	-2.087121723	0.044678652	-0.106283128	-0.0013565	-0

SUMMARY OUTPUT FOR Subgroup Age <30 where VV is predicted by N							
Regression Statistics							
Multiple R	0.311388826	Correlation between VV and N is NOT significant at p = 0.05 for Subgroup Age <30					
R Square	0.096963001						
Adjusted R Square	0.069598244						
Standard Error	3.530696792						
Observations	35						
ANOVA							
	df	*SS*	*MS*	*F*	*Significance F*		
Regression	1	44.17080263	44.17080263	3.543353203	0.068627048		
Residual	33	411.3720545	12.46581983				
Total	34	455.5428571					
	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lowe*
Intercept	7.091931147	1.117131804	6.348338774	3.47346E-07	4.8191076	9.364754693	4.
Neuroticism	-0.040959572	0.021759464	-1.882379665	0.068627048	-0.085229569	0.003310425	-0.08

SUMMARY OUTPUT FOR Subgroup Age <30 where SG is predicted by A							
Regression Statistics							
Multiple R	0.14328183	Correlation between SG and A is NOT significant at p = 0.05 for Subgroup Age <30					
R Square	0.020529683						
Adjusted R Square	-0.009151236						
Standard Error	4.003036847						
Observations	35						
ANOVA							
	df	*SS*	*MS*	*F*	*Significance F*		
Regression	1	11.0836824	11.0836824	0.691679489	0.411571555		
Residual	33	528.8020319	16.024304				
Total	34	539.8857143					
	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lowe*
Intercept	10.79276605	1.523923396	7.082223479	4.15353E-08	7.692318135	13.89321397	7.69
Agreeableness	-0.022712464	0.027309378	-0.831672705	0.411571555	-0.078273854	0.032848927	-0.07

SUMMARY OUTPUT FOR Subgroup Age 30+ where AR is predicted by E

Regression Statistics		
Multiple R	0.67043438	Correlation between AR and E is significant at p = 0.001 for Subgroup Age 30+
R Square	0.449482258	
Adjusted R Square	0.434994949	
Standard Error	4.194447288	
Observations	40	

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	545.8512541	545.8512541	31.02593159	2.21331E-06
Residual	38	668.5487459	17.59338805		
Total	39	1214.4			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*
Intercept	16.75293635	1.350507196	12.40492194	6.20448E-15	14.01897737	19.48689533
Extraversion	-0.128363102	0.023045057	-5.570092601	2.21331E-06	-0.175015382	-0.081710821

SUMMARY OUTPUT FOR Subgroup Age 30+ where SI is predicted by O

Regression Statistics		
Multiple R	0.555469307	Correlation between SI and O is significant at p = 0.001 for Subgroup Age 30+
R Square	0.308546151	
Adjusted R Square	0.290349998	
Standard Error	5.733195655	
Observations	40	

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	557.3577679	557.3577679	16.95666859	0.000198752
Residual	38	1249.042232	32.86953242		
Total	39	1806.4			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lo*
Intercept	4.076461747	1.659414392	2.456566464	0.018708024	0.717152818	7.435770675	0
Openness	0.12905385	0.031340123	4.117847567	0.000198752	0.065609085	0.192498615	0

SUMMARY OUTPUT FOR Subgroup Age 30+ where VV is predicted by O

Regression Statistics		
Multiple R	0.370735163	Correlation between VV and O is significant at p = 0.05 for Subgroup Age 30+
R Square	0.137444561	
Adjusted R Square	0.114745733	
Standard Error	4.951006327	
Observations	40	

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	148.4263812	148.4263812	6.055139268	0.018522996
Residual	38	931.4736188	24.51246365		
Total	39	1079.9			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*
Intercept	10.00360973	1.433017753	6.980799581	2.6109E-08	7.102616853	12.90460261
Openness	-0.066597739	0.027064339	-2.460719258	0.018522996	-0.12138663	-0.011808848

SUMMARY OUTPUT FOR Subgroup Age 30+ where SG is predicted by E							
Regression Statistics							
Multiple R	0.270358007	Correlation between SG and E is NOT significant at p = 0.05 for Subgroup Age 30+					
R Square	0.073093452						
Adjusted R Square	0.048701174						
Standard Error	4.5262649						
Observations	40						
ANOVA							
	df	*SS*	*MS*	*F*	*Significance F*		
Regression	1	61.39119021	61.39119021	2.996581668	0.091553849		
Residual	38	778.5088098	20.48707394				
Total	39	839.9					
	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lowe*
Intercept	13.24761606	1.457344174	9.090245321	4.51384E-11	10.29737691	16.1978552	10.2
Extraversion	-0.043048307	0.024868123	-1.731063739	0.091553849	-0.093391192	0.007294579	-0.09

SUMMARY OUTPUT FOR Subgroup Male where AR is predicted by E						
Regression Statistics						
Multiple R	0.67278327	Correlation between AR and E is significant at p = 0.001 for Subgroup Male				
R Square	0.452637328					
Adjusted R Square	0.441466661					
Standard Error	4.266232499					
Observations	51					
ANOVA						
	df	*SS*	*MS*	*F*	*Significance F*	
Regression	1	737.4970863	737.4970863	40.52017099	6.37857E-08	
Residual	49	891.836247	18.20073974			
Total	50	1629.333333				
	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*
Intercept	17.52276698	1.141187892	15.35484831	2.33626E-20	15.22946544	19.81606851
Extraversion	-0.136354694	0.021420739	-6.365545616	6.37857E-08	-0.179401255	-0.093308132

SUMMARY OUTPUT FOR Subgroup Male where SI is predicted by O						
Regression Statistics						
Multiple R	0.378266267	Correlation between SI and O is significant at p = 0.01 for Subgroup Male				
R Square	0.143085369					
Adjusted R Square	0.125597315					
Standard Error	5.241244721					
Observations	51					
ANOVA						
	df	*SS*	*MS*	*F*	*Significance F*	
Regression	1	224.7618645	224.7618645	8.181892142	0.006202139	
Residual	49	1346.061665	27.47064622			
Total	50	1570.823529				
	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*
Intercept	5.642533538	1.401815731	4.025160664	0.000197045	2.825481067	8.459586009
Openness	0.075785467	0.026494703	2.860400696	0.006202139	0.0225424	0.129028535

SUMMARY OUTPUT FOR Subgroup Male where VV is predicted by E						
Regression Statistics						
Multiple R	0.152849143	Correlation between VV and E is NOT significant at p = 0.05 for Subgroup Male				
R Square	0.02336286					
Adjusted R Square	0.00343149					
Standard Error	4.943343148					
Observations	51					
ANOVA						
	df	*SS*	*MS*	*F*	*Significance F*	
Regression	1	28.64378302	28.64378302	1.172165293	0.284255937	
Residual	49	1197.395433	24.43664148			
Total	50	1226.039216				
	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*
Intercept	7.415870891	1.32231034	5.608268093	9.33723E-07	4.758590387	10.0731514
Extraversion	-0.026872318	0.02482051	-1.082665827	0.284255937	-0.076750969	0.023006334

SUMMARY OUTPUT FOR Subgroup Male where SG is predicted by C							
Regression Statistics							
Multiple R	0.11926919	Correlation between SG and C is NOT significant at p = 0.05 for Subgroup Male					
R Square	0.01422514						
Adjusted R Square	-0.005892715						
Standard Error	4.748117498						
Observations	51						
ANOVA							
	df	*SS*	*MS*	*F*	*Significance F*		
Regression	1	15.94108196	15.94108196	0.7070903	0.40449631		
Residual	49	1104.686369	22.54461978				
Total	50	1120.627451					
	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lc*
Intercept	9.116746953	2.091592293	4.358759105	6.68747E-05	4.913537424	13.31995648	4
Conscientiousness	0.024264167	0.028855456	0.840886615	0.40449631	-0.033723008	0.082251342	-(

SUMMARY OUTPUT FOR Subgroup Male where SG is predicted by E							
Regression Statistics							
Multiple R	0.143642373	Correlation between SG and E is NOT significant at p = 0.05 for Subgroup Male					
R Square	0.020633131						
Adjusted R Square	0.000646052						
Standard Error	4.732659859						
Observations	51						
ANOVA							
	df	*SS*	*MS*	*F*	*Significance F*		
Regression	1	23.12205348	23.12205348	1.032323507	0.314604328		
Residual	49	1097.505397	22.39806934				
Total	50	1120.627451					
	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lc*
Intercept	11.88024661	1.265954007	9.384421976	1.58849E-12	9.336218326	14.42427489	9
Extraversion	-0.024143662	0.02376267	-1.016033221	0.314604328	-0.071896505	0.023609182	-(

SUMMARY OUTPUT FOR Subgroup Female where AR is predicted by E

Regression Statistics		
Multiple R	0.623497861	Correlation between AR and E is significant at p = 0.01 for Subgroup Female
R Square	0.388749582	
Adjusted R Square	0.360965472	
Standard Error	3.463828054	
Observations	24	

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	167.875028	167.875	13.9918	0.001133169
Residual	22	263.9583054	11.9981		
Total	23	431.8333333			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower*
Intercept	15.82998381	1.491732826	10.61181	4.05E-10	12.73631596	18.92365166	12.73
Extraversion	-0.09673471	0.025861018	-3.74056	0.001133	-0.150367236	-0.043102184	-0.150

SUMMARY OUTPUT FOR Subgroup Female where SI is predicted by O

Regression Statistics		
Multiple R	0.548432132	Correlation between SI and O is significant at p = 0.01 for Subgroup Female
R Square	0.300777803	
Adjusted R Square	0.268994976	
Standard Error	5.264468182	
Observations	24	

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	262.2782446	262.2782446	9.463532064	0.005522664
Residual	22	609.7217554	27.71462524		
Total	23	872			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*
Intercept	3.989495798	1.951309092	2.044522734	0.053050573	-0.057275917	8.036267514
Openness	0.123716153	0.040216084	3.076285433	0.005522664	0.04031301	0.207119296

SUMMARY OUTPUT FOR Subgroup Female where VV is predicted by E

Regression Statistics		
Multiple R	0.424333912	Correlation between VV and E is significant at p = 0.05 for Subgroup Female
R Square	0.180059269	
Adjusted R Square	0.142789235	
Standard Error	3.689984482	
Observations	24	

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	65.78165284	65.78165284	4.831207624	0.038767168
Residual	22	299.5516805	13.61598548		
Total	23	365.3333333			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*
Intercept	9.408963696	1.589129394	5.920829185	5.8632E-06	6.113307507	12.70461989
Extraversion	-0.060553838	0.027549507	-2.198000824	0.038767168	-0.117688079	-0.003419597

SUMMARY OUTPUT FOR Subgroup Female where SG is predicted by O							
Regression Statistics							
Multiple R	0.328503615	Correlation between SG and O is NOT significant at p = 0.05 for Subgroup Female					
R Square	0.107914625						
Adjusted R Square	0.06736529						
Standard Error	3.320039301						
Observations	24						
ANOVA							
	df	*SS*	*MS*	*F*	*Significance F*		
Regression	1	29.33479225	29.33479	2.661316751	0.117049403		
Residual	22	242.4985411	11.02266				
Total	23	271.8333333					
	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95*
Intercept	7.90765056	1.230593984	6.425881	1.82456E-06	5.355552101	10.45974902	5.35555
Openness	0.041374883	0.025362292	1.631354	0.117049403	-0.011223347	0.093973114	-0.01122

SUMMARY OUTPUT FOR Subgroup High School where AR is predicted by E							
Regression Statistics							
Multiple R	0.626414501	Correlation between AR and E is significant at p = 0.01 for Subgroup High School					
R Square	0.392395126						
Adjusted R Square	0.351888135						
Standard Error	4.736676873						
Observations	17						
ANOVA							
	df	*SS*	*MS*	*F*	*Significance F*		
Regression	1	217.3407359	217.3407359	9.687096259	0.007134043		
Residual	15	336.541617	22.4361078				
Total	16	553.8823529					
	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lo*
Intercept	18.15408865	1.848436383	9.821321859	6.33128E-08	14.21423734	22.09393997	1
Extraversion	-0.133251317	0.042812905	-3.11241004	0.007134043	-0.224504921	-0.041997713	-0

SUMMARY OUTPUT FOR Subgroup High School where SI is predicted by O							
Regression Statistics							
Multiple R	0.434457147	Correlation between SI and O is NOT significant at p = 0.05 for Subgroup High School					
R Square	0.188753013						
Adjusted R Square	0.13466988						
Standard Error	3.933718166						
Observations	17						
ANOVA							
	df	*SS*	*MS*	*F*	*Significance F*		
Regression	1	54.00556787	54.00556787	3.490053257	0.081397963		
Residual	15	232.1120792	15.47413861				
Total	16	286.1176471					
	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 9*
Intercept	4.503624196	1.825786466	2.466676296	0.02616916	0.612050072	8.395198321	0.61205
Openness	0.081987378	0.043886502	1.868168423	0.081397963	-0.011554545	0.1755293	-0.01155

SUMMARY OUTPUT FOR Subgroup High School where VV is predicted by E

Regression Statistics	
Multiple R	0.361955912
R Square	0.131012082
Adjusted R Square	0.073079554
Standard Error	2.787431493
Observations	17

Correlation between VV and E is NOT significant at p = 0.05 for Subgroup High School

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	17.57103217	17.57103217	2.261459783	0.153390604
Residual	15	116.5466149	7.769774326		
Total	16	134.1176471			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 9*
Intercept	6.693264388	1.087764676	6.153228297	1.84747E-05	4.374747438	9.011781339	4.3747
Extraversion	-0.037887817	0.025194465	-1.503815076	0.153390604	-0.091588581	0.015812948	-0.0915

SUMMARY OUTPUT FOR Subgroup High School where SG is predicted by E

Regression Statistics	
Multiple R	0.123178883
R Square	0.015173037
Adjusted R Square	-0.050482094
Standard Error	4.129756137
Observations	17

Correlation between SGand E is NOT significant at p = 0.05 for Subgroup High School

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	3.94141958	3.94141958	0.231102081	0.637644224
Residual	15	255.8232863	17.05488575		
Total	16	259.7647059			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 9*
Intercept	9.275412326	1.611592199	5.75543387	3.7994E-05	5.840382754	12.7104419	5.8403
Extraversion	0.017944331	0.037327195	0.480730778	0.637644224	-0.061616749	0.097505412	-0.0616

SUMMARY OUTPUT FOR Subgroup Bachelors where AR is predicted by E

Regression Statistics	
Multiple R	0.581826104
R Square	0.338521615
Adjusted R Square	0.317850416
Standard Error	3.737494758
Observations	34

Correlation between AR and E is significant at p = 0.001 for Subgroup Bachelors

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	228.7609599	228.7609599	16.37648628	0.000307033
Residual	32	447.003746	13.96886706		
Total	33	675.7647059			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lo*
Intercept	15.25261945	1.526300943	9.993192708	2.30521E-11	12.1436488	18.3615901	
Extraversion	-0.099941826	0.024696586	-4.046787156	0.000307033	-0.150247082	-0.049636569	-0

SUMMARY OUTPUT FOR Subgroup Bachelors where SI is predicted by O

Regression Statistics		
Multiple R	0.486708592	Correlation between SI and O is significant at p = 0.01 for Subgroup Bachelors
R Square	0.236885254	
Adjusted R Square	0.213037918	
Standard Error	5.272606797	
Observations	34	

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	276.1524681	276.1524681	9.933405367	0.003512569
Residual	32	889.6122378	27.80038243		
Total	33	1165.764706			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lo*
Intercept	4.098490222	1.703078504	2.406518674	0.022052433	0.629435769	7.567544676	0
Openness	0.097264989	0.03086082	3.151730535	0.003512569	0.034403609	0.160126369	0

SUMMARY OUTPUT FOR Subgroup Bachelors where VV is predicted by E

Regression Statistics		
Multiple R	0.131200727	Correlation between VV and E is NOT significant at p = 0.05 for Subgroup Bachelors
R Square	0.017213631	
Adjusted R Square	-0.013498443	
Standard Error	4.546540709	
Observations	34	

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	11.58578602	11.58578602	0.560484149	0.459532996
Residual	32	661.4730375	20.67103242		
Total	33	673.0588235			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lowe*
Intercept	6.967392798	1.856695413	3.752577159	0.000698029	3.185431205	10.74935439	3.18
Extraversion	-0.022491534	0.030042593	-0.748654893	0.459532996	-0.083686241	0.038703173	-0.08

SUMMARY OUTPUT FOR Subgroup Bachelors where SG is predicted by O

Regression Statistics		
Multiple R	0.350680835	Correlation between SG and O is significant at p = 0.05 for Subgroup Bachelors
R Square	0.122977048	
Adjusted R Square	0.095570081	
Standard Error	4.394018927	
Observations	34	

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	86.63371355	86.63371355	4.487072474	0.042011668
Residual	32	617.8368747	19.30740233		
Total	33	704.4705882			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lo*
Intercept	6.98173838	1.419290205	4.919176048	2.51305E-05	4.090741286	9.872735475	4
Openness	0.05447855	0.025718403	2.118271105	0.042011668	0.002091922	0.106865179	0

SUMMARY OUTPUT FOR Subgroup Masters+ where AR is predicted by E							
Regression Statistics							
Multiple R	0.664592962	Correlation between AR and E is significant at p = 0.001 for Subgroup Masters+					
R Square	0.441683805						
Adjusted R Square	0.416305796						
Standard Error	4.046884611						
Observations	24						
ANOVA							
	df	*SS*	*MS*	*F*	*Significance F*		
Regression	1	285.0332822	285.0332822	17.40419461	0.000396566		
Residual	22	360.3000512	16.37727505				
Total	23	645.3333333					
	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lc*
Intercept	17.35263096	1.593736346	10.88801859	2.51192E-10	14.04742053	20.65784139	1
Extraversion	-0.129717817	0.031093719	-4.171833483	0.000396566	-0.194202311	-0.065233322	-(

SUMMARY OUTPUT FOR Subgroup Masters+ where SI is predicted by O							
Regression Statistics							
Multiple R	0.343565157	Correlation between SI and O is NOT significant at p = 0.05 for Subgroup Masters+					
R Square	0.118037017						
Adjusted R Square	0.077947791						
Standard Error	5.90742513						
Observations	24						
ANOVA							
	df	*SS*	*MS*	*F*	*Significance F*		
Regression	1	102.7512233	102.7512233	2.944357557	0.100228889		
Residual	22	767.7487767	34.89767167				
Total	23	870.5					
	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lowe*
Intercept	7.345173407	2.321934147	3.163385756	0.004503807	2.529771545	12.16057527	2.52
Openness	0.075803189	0.044176592	1.715913039	0.100228889	-0.015813552	0.167419931	-0.01

SUMMARY OUTPUT FOR Subgroup Masters+ where VV is predicted by O						
Regression Statistics						
Multiple R	0.438947521	Correlation between VV and O is significant at p = 0.05 for Subgroup Masters+				
R Square	0.192674926					
Adjusted R Square	0.155978332					
Standard Error	5.139594515					
Observations	24					
ANOVA						
	df	*SS*	*MS*	*F*	*Significance F*	
Regression	1	138.6938342	138.6938342	5.250485223	0.031883153	
Residual	22	581.1394991	26.41543178			
Total	23	719.8333333				
	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*
Intercept	11.53909461	2.020135633	5.712039539	9.57946E-06	7.349585232	15.72860399
Openness	-0.088068897	0.038434642	-2.291393729	0.031883153	-0.16777755	-0.008360243

SUMMARY OUTPUT FOR Subgroup Masters+ where SG is predicted by O							
Regression Statistics							
Multiple R	0.096956702	Correlation between SG and O is NOT significant at p = 0.05 for Subgroup Masters+					
R Square	0.009400602						
Adjusted R Square	-0.035626643						
Standard Error	4.026140625						
Observations	24						
ANOVA							
	df	*SS*	*MS*	*F*	*Significance F*		
Regression	1	3.384216756	3.384216756	0.208775865	0.652208179		
Residual	22	356.6157832	16.20980833				
Total	23	360					
	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lowe*
Intercept	11.38208237	1.58248868	7.192520564	3.29418E-07	8.100198198	14.66396655	8.10
Openness	0.013756979	0.03010807	0.456919977	0.652208179	-0.048683404	0.076197361	-0.04

SUMMARY OUTPUT FOR Subgroup Masters+ where SG is predicted by E							
Regression Statistics							
Multiple R	0.208143911	Correlation between SG and E is NOT significant at p = 0.05 for Subgroup Masters+					
R Square	0.043323888						
Adjusted R Square	-0.00016139						
Standard Error	3.95660208						
Observations	24						
ANOVA							
	df	*SS*	*MS*	*F*	*Significance F*		
Regression	1	15.59659963	15.59659963	0.99628863	0.329062909		
Residual	22	344.4034004	15.65470002				
Total	23	360					
	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lowe*
Intercept	13.33006021	1.558181452	8.554883127	1.90511E-08	10.0985862	16.56153423	10
Extraversion	-0.030343579	0.030400044	-0.99814259	0.329062909	-0.09338948	0.032702322	-0.0

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