

**THE EFFECTS OF BIOGRAPHICAL DATA ON THE PREDICTION
OF DOMAIN KNOWLEDGE**

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OF DOMAIN KNOWLEDGE**

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SUMMARY

This study examined the effects of life experience information on the prediction of domain knowledge. Specifically, it was hypothesized that individuals with a higher level of experience within a domain would have a higher level of domain knowledge, and that attribution of experience (e.g., educational experience, extracurricular experience, etc) would influence the type of domain knowledge assessment on which an individual was most successful (e.g., open-ended scenarios vs. multiple-choice questions). In order to test these hypotheses, participants completed a biodata measure, various ability and non-ability measures, and a set of domain knowledge tests. Hypotheses were evaluated in the context of regressions and structural equation modeling. Results showed that biodata had significant predictive validity for domain knowledge.

CHAPTER 1

INTRODUCTION

The use of life experience information, often referred to as biodata, in selection and performance research is supported by the evidence that an individual's future behavior is strongly influenced by his/her actions in the past (Owens, 1976; Owens & Schoenfeldt, 1979), such that past behaviors and experiences can be used to predict future behaviors and experiences. This does not imply that future events will replicate past events, but that they are conditioned by the past such that learning, heredity, and environmental circumstances affect the likelihood of a specific behavior in a new situation (Mumford & Stokes, 1992). Nickels (1994) suggested that "biodata measures may predict performance across so many aspects of behavior as well as they do because responses to biodata items may serve to capture previous manifestations of the constructs and mechanisms that ultimately determine predictive relationships with criteria" (p. 2).

The purpose of the current study was to begin to delineate the construct of biodata and apply the use of life experience information to the prediction of domain knowledge. This paper will begin with a general overview of the domain of biodata, and will include some discussion of past research and obstacles to progress within the domain. Next, the paper will explore the various scaling approaches that have been used in the construction of biodata measures, and the benefits of using biodata measures as predictors of performance. An existing model of biodata will be evaluated and applied to the prediction of domain knowledge through the development of a biodata questionnaire.

The prevailing notion within biodata research is that evaluating individuals in terms of past experiences and behaviors will help predict how that individual will

perform in the future, and may help uncover aspects from the individual's past that might propel or hinder his/her success in a particular organization. Mumford and Owens (1987) suggested that construction of any background data measure should include a focus on the developmental antecedents of effective job performance.

Nickels (1994) stated that "it is necessary to attain an understanding of the kind of constructs contributing to the predictive power of biodata measures" (p. 14). In other words, a goal in biodata research should be an attempt to uncover the fundamental constructs underlying experience that lead to the explanation and prediction of future behavior. While the underlying construct of biodata has been delineated in some research (e.g., Mael, 1991), I argue that it has not been sufficiently articulated in much of the literature within the domain.

Previous Findings

Research on life experience information has found biodata measures to have average predictive validities ranging from $r = .3$ -.4 for a variety of performance domains, including leadership performance (e.g., Russell, Mattson, Devlin, & Atwater, 1990) and salesperson performance (e.g., Stokes, Toth, Searcy, Stroupe, & Carter, 1999). Despite this finding, organizations remain hesitant to implement biodata measures in their selection procedures. According to Mael, Connerley, and Morath (1996), a survey of personnel specialists found that only 4% of respondents used biodata, citing invasion of privacy as one of the major reasons for avoiding the use of biodata in their organizations. Some researchers have argued that the lack of established construct validity and alleged atheoretical nature of life experiences information has impeded the use of biodata in personnel selection and performance prediction among Industrial-Organizational psychologists (e.g., Dean, Russell, & Muchinsky, 1999; Stokes & Cooper, 2001).

Obstacles to advancement in the domain

There is substantial lack of agreement regarding a definition of what constitutes a biodata item, as well as a limited understanding of what biodata items measure, and how they obtain their predictive power. Mumford and Stokes (1991, 1992) suggested that biodata items encompass a wider range of behaviors than those obtained with a demographics questionnaire, capturing interests, skills, aptitudes, abilities, and personality variables that condition entry into, and performance in, various situations. Biodata refers to experiential information that attempts to uncover regular patterns of behavior, whereas demographics information is often categorical and concerns sorting individuals into groups. In contrast, the use of biodata is centered on making predictions for future behavior.

There are various types of biodata reported in the literature. In the most classic interpretation, biodata items refer to objective, retrospective statements about discrete experiences that may have occurred in an individual's past. In line with this interpretation, Mael (1991) proposed a list of 10 attributes that could be used to classify biodata items including: history, externality, objectivity, first handedness, discreteness, verifiability, controllability, equal accessibility, job relevance, and invasiveness. Mael provided the following items as potential biodata questions: "1) How old were you when you got your first paying job?; 2) Did you ever get fired from a job?; 3) How many hours did you study for your real-estate license test?; 4) How many tries did it take you to pass the CPA exam?; 5) Were you ever class president?" (Mael, 1991, p.773). Many of these items appear in an objective Yes/No format, leaving little room for subjective interpretation as to the nature of the question.

The type of biodata that is used most often, most notably in Owens (1979) Biographical Questionnaire (BQ), includes items that are close to the classic definition in that they refer to objective statements about discrete experiences that have occurred in the individual's past. However, there are a few departures, such that items may refer to the regularity or frequency of behaviors over time. These types of items involve some element of judgment, and Likert-type response scales that allow the individual to provide an aggregated estimate of the specified behavior over time.

Recent conceptualizations of biodata offer more extreme departures from early definitions. For example, Oswald, Schmitt, Kim, Ramsay, and Gillespie (2004) defined the domain of biodata as encompassing past beliefs and attitudes, as well as behaviorally based experiences. Sample questions from their biodata measure include: "1) If you were leaving a concert and noticed that someone left their purse behind with no identification, what would you do? [answer choices included: make an effort to find the person in the area, then turn the purse and its contents over to a charity if you fail; make an effort to find the owner, if you fail, keep the cash in the purse for yourself and give the purse to a friend; keep the cash and purse; turn the purse over to the facility's lost and found]; 2) Think about the last several times you have had to learn new concepts about something. How much did you tend to learn? [usually not enough; sometimes not enough; just what is needed; a little more than what is needed; much more than what is needed]" (p.204). These items often ask about the expectation of a behavior, as well as attitudes and beliefs, rather than the behavior itself. Items may have a future-orientation, and they are typically presented in a best-judgment format, requiring the participant to choose between responses to certain (often, hypothetical) situations.

I suggest that the former set of questions suggested by Mael (1991) more appropriately target the domain of biodata in their emphasis on objective life experience information. The set of biodata questions used by Oswald et al. (2004) may be confounded by the added emphasis on beliefs and attitudes. With their measure, it may be difficult to ascertain the added value of biodata over and above existing measures of personality, interests, and attitudes. An objective measure of life experience information that focuses on verifiable and historical life experiences without the confounding of beliefs and attitudes will enable the underlying constructs of biodata to be delineated more clearly. Using an objective background data measure will help researchers understand the factors underlying experience that allow biodata measures to successfully predict future performance. It seems that the disparity between definitions of biodata will continue to hamper significant advances with the domain, since it is difficult to evaluate the fundamental nature of a biodata item without a solid understanding of what constitutes biodata. Gaining an understanding of the underlying behavioral constructs of life experiences may enable researchers to come to a consensus regarding a definition of what constitutes a biodata item.

With regards to the perceived invasiveness of biodata items, Mael et al. (1996) found that items that were more verifiable and impersonal were seen as less invasive. Thus, the use of objective, verifiable, and impersonal items may help clarify the fundamental nature of biodata items and eliminate concerns regarding invasion of privacy simultaneously.

Scaling Methods

Proponents of biodata have debated the use of various methods for scaling biodata measures. These methods include empirical (e.g., Hogan, 1994), rational (e.g., Hough & Paullin, 1994), factorial (e.g., Schoenfeldt & Mendoza, 1994), and sub-grouping (e.g., Owens & Schoenfeldt, 1979) approaches. With the empirical approach, items are included in a measure based on empirical evidence that they differentiate between upper and lower performing groups on a specific criterion, and are then weighted according to the direction and strength of the relationship. According to Guion (1965), the empirical approach is most commonly used when the primary purpose is to maximize prediction of an external criterion. As a result, this method is often criticized for its “dustbowl empiricism” and lack of contribution to knowledge and theory development (Hogan, 1994). The utility of an empirical approach is demonstrated through strong prediction of criterion performance, despite the fact that there is no reference to broader theory. Thus, conclusions drawn from empirically derived scores are often limited (Hogan, 1994). Despite this criticism, Rothstein, Schmidt, Erwin, Owens & Sparks (1990) found an empirically developed biodata measure demonstrated validities that were generalizable and stable across time, lending some support to the use of an empirical approach.

In using the rational approach, items are selected for inclusion in a measure based on an assumed relevance of the item to an underlying trait based on existing theory. The use of a rational approach is based upon an assumption that the test developer has substantial knowledge about the relationship between the specific item and corresponding traits. Hough and Paullin (1994) acknowledged that a potential issue with the rational keying approach is that it fails to account for subtle items that may not overtly correlate

with an underlying construct. The benefit of subtle items is that individuals are typically unsure of the “correct” answer, thus at least in theory; socially desirable responding and response distortion is minimized.

The factorial approach to scaling biodata measures is based on the idea that a structure of individual differences can be inferred through factor analysis. This approach is a statistical method by which a large number of individual item responses is reduced to a smaller set of factors (Schoenfeldt & Mendoza, 1994). In factor analysis, the main purpose is to identify common constructs in a large number of measures and to derive a set of underlying hypothesized factors from the original set of items.

The subgrouping approach was developed by Owens (1968, 1971, and 1976) as an alternative scaling procedure. This approach stems from Owen’s belief that a biodata measure could be created to identify life history patterns without regard to a specific criterion, thus producing a more general predictive system (Hein & Wesley, 1994). The subgrouping approach is statistically based and categorizes people in groups based on similar patterns of behavior and experience. The rationale for this approach is from a study by Owens and Schoenfeldt (1979). They suggest that 73% of individuals can be described by assignment to a single subgroup. Some examples of these subgroups include “indifferent low-achieving artists”; “cognitively simple, non-achieving business majors”; “analytical independents”; and “cognitively complex religious converters” (Owens & Schoenfeldt, 1979). The subgrouping approach may not be feasible for use in all situations, as it requires a significant amount of time and a large sample size.

There are different reasons for using each of the methods for scaling biodata measures. While the empirical approach has a great deal of predictive power, it may not

advance knowledge or understanding of the observed relationships. In contrast, the rational approach has less predictive power, but may allow for greater understanding and the development of scientific theory.

CHAPTER 2

THE ADDED VALUE OF BIODATA

Traditionally, research within the domain of individual differences has focused on the cognitive, conative, and affective determinants of performance (e.g., see Ackerman, Kanfer, and Goff, 1995). Demonstrating the utility of biodata rests upon the value that the biodata measure adds to performance prediction, over and above what is already established through existing measures. That is, how much does the biodata measure add to the prediction of performance over the trait measures? Understanding the added value of biodata is essential to progress within the domain. I suggest that biodata measures reveal information about an individual beyond what is obtained through existing affective, cognitive, and conative measures in their focus on discrete life experiences. Since biodata items reflect individual differences in experiences in combination with situational constraints, life experience information can be helpful in developing a more complete and accurate understanding of an individual.

Biodata researchers have consistently argued that biodata does in fact provide information beyond that obtained with traditional personality measures (e.g., Mumford & Stokes, 1992). I suggest that while personality traits represent individual tendencies given few constraints, biodata items capture the experiences that may not be under volitional control, but are influential regardless (e.g., parental warmth, education), and may have implications for future behavior. Thus, biodata should provide predictive validity over and above existing trait measures.

McManus and Kelly (1999) administered a biodata measure, and found that the measure provided incremental predictive validity over and above a personality measure

for the prediction of contextual performance. They also found that a personality measure did not provide incremental predictive validity over and above the biodata measure in the prediction of sales performance. As a result, they suggest using both personality and biodata measures for optimal prediction. Furthermore, Owens and Schoenfeldt (1979) highlighted the importance of studying both biodata *and* personality in that “rational conviction and prior research suggest the vital role of experience in the development of personality” (p.562), implicating life experiences as a cause and a consequence in the development of personality and interests.

In evaluating the incremental predictive validity of a biodata measure over and above General Mental Ability (GMA), Mount, Witt, and Barrick (2000) found that biodata predictors could account for incremental variance in the criterion over and above that accounted for by GMA. They evaluated the use of GMA, biodata, and personality as predictors of: quantity/ quality of work, problem solving, interpersonal facilitation, and retention probability, finding that the biodata measure accounted for about 5% of the incremental variance in quantity/ quality of work, interpersonal facilitation, and retention probability. While the biodata predictors did not have significant predictive validity for problem-solving, personality and GMA did show significant predictive validity. The findings by McManus & Kelly (1999) and Mount, Witt, and Barrick (2000) suggest that biodata measures are capturing information that is not obtained through existing measures, providing an impetus for additional research on the underlying constructs of past behavior and experience that can be used to predict future performance.

CHAPTER 3

MODELS OF BIODATA

The Ecology Model

To date, the Ecology model is the only clear model of biodata (see Figure 1).

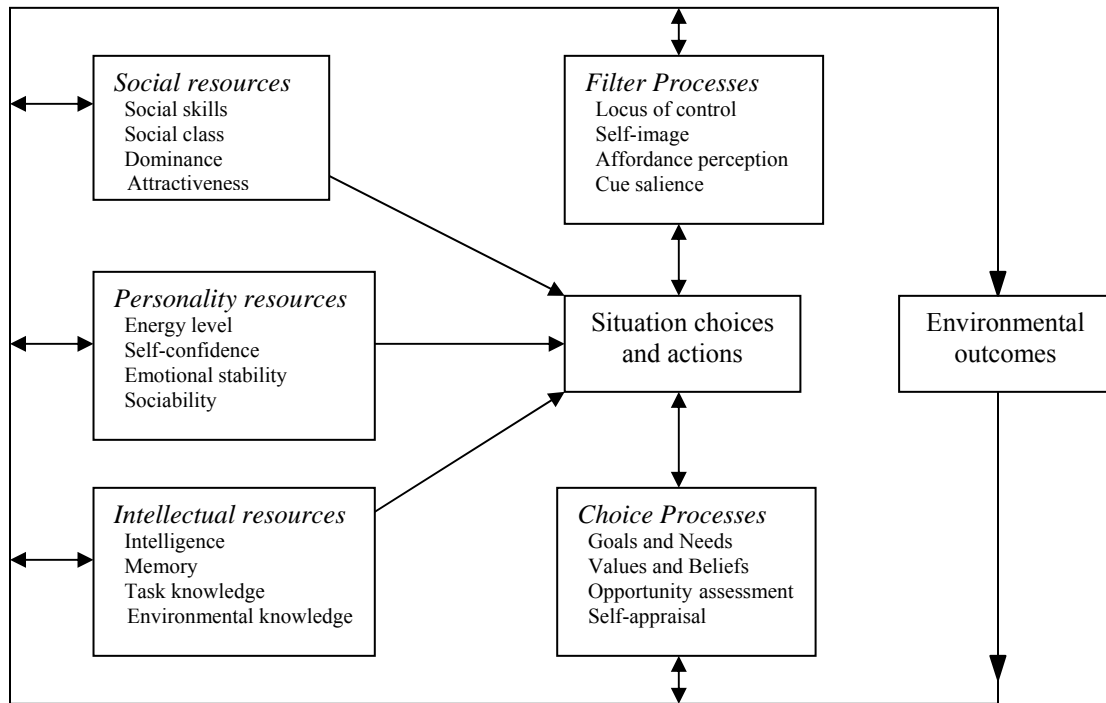


Figure 1. The Ecology Model

Developed by Mumford, Stokes, and Owens (1990), the Ecology model is the first comprehensive model for biodata and provides a theoretical rationale for its use. Similar to other perspectives that emphasize successful adaptation, this model represents the idea that individuals have unique characteristics and experiences resulting in individual differences, which then influence the choices that the individual makes. The Ecology model is based on an assumption that the individual is an active entity who wants to maximize adaptation to changing environmental demands (Mumford & Stokes, 1992), with the ultimate goal of long term adaptation. Additionally, this model shows the importance of situational choice on developmental patterns.

An additional component of the Ecology model is that behavior is often prompted by the reward value of certain actions, which may suggest the impact of motivation on these patterns. Specifically, certain experiences represent an attraction/ willingness to devote energy to situations offering some reward. The model assumes that the individual will seek out situations that will maximize his/her needs and values, based on the perceived value of the outcome. Mael (1991) suggested that this situational choice is an iterative process through which the individual develops a cohesive pattern of choices over time. This profile of choices can be used as an effective predictor of future choices and behavioral patterns.

Support for a new model

Owens and Schoenfeldt (1979) proposed two categories of variables within the domain of life experiences: input variables and prior behaviors. Input variables are things that are done to a person, including exposure to certain situations. Input variables include such factors as parental warmth, parental beliefs, or community characteristics; resources and choices that are not under individual control. In contrast, prior behavior variables include past activities, reactions to past situations, and preferences for activities and actions that are assumed to be under volitional control. Mael (1991) suggested that prior behavior variables are the main focus of the Ecology model. He suggested that future studies use the Social Identity Theory as a complementary model, to include a focus on input variables within a comprehensive model of biodata.

Social Identity Theory

According to Mael (1991), every individual has a self-concept which is comprised of a personal identity and a social identity. The personal identity refers to attributes that are specific to each individual, while the social identity includes the perceived aspects of

a person that define him/her as belonging to a particular social category. According to this perspective, experiences that categorize a person as belonging to a perceived social category have the power to influence his/her future behavioral patterns. Mael (1991) stated that “when a person associates with a team, club, school, or any other psychological group, the person takes on (to varying degrees) the syndrome of aspirations, preferences, values, and self-perceptions that are endemic to group members... Thus, biodata items encompass not only the choice-based, adaptive responses of the individual, but also the effects of all characteristics internalized through identification with the myriad psychosocial entities with whom one interacts throughout life” (p. 768). According to Mael’s (1991) definition, biodata items may assess aspects of an individual’s environment that are unaffected by the individual, but still have an impact on that individual. Research within the domain of biodata may benefit from the inclusion of both input variables as well as prior behaviors in a more comprehensive model of life experiences. This would enable researchers to evaluate different types of experience (i.e., those under and not under volitional control), and their influence on cognitive, conative, and affective traits as well as performance prediction.

CHAPTER 4

DOMAIN KNOWLEDGE

Biodata research has typically evaluated life experience information in the context of performance prediction. Although researchers within the area of domain knowledge agree that knowledge is an important aspect of job performance (e.g., see Kuncel, Hezlett, and Ones, 2004; Colquitt, LePine, and Noe, 2000), no investigations to date have determined the utility of a biodata measure in predicting domain knowledge.

In much of the intelligence literature, there has been criticism against the use of typical intelligence tests for measuring adult intelligence. For example, Ackerman (1996) cites Terman's discussion of the problems associated with measuring adult intelligence in terms of IQ. Traditional tests of intelligence such as the Wechsler Adult Intelligence Scale-Revised (WAIS-R) place a small emphasis on declarative knowledge, (Ackerman, 1996) resulting in a peak in intelligence in the mid-twenties, followed by a decrease in intelligence into adulthood. Despite the negative outlook for adult intelligence, many adults continue to function successfully in their occupational and avocational activities well past their mid-twenties. As discussed in Ackerman (1996), Cattell (1943) originally differentiated between fluid and crystallized intelligence. Cattell suggested that fluid intelligence refers to the more innate aspects of intelligence, while crystallized intelligence refers to knowledge gained through educational, occupational, and avocational experiences. In addition, Cattell developed his Investment Theory, in which he describes how crystallized intelligence (Gc) develops out of fluid intelligence (Gf) as a function of time and investment.

Based in part on Cattell's Investment Theory, Ackerman (1996) proposed the Intelligence-as-process, Personality, Interests, and Intelligence-as-knowledge (PPIK) theory of adult intellectual development. The PPIK theory refers to the transformation of intelligence-as-process into intelligence-as-knowledge through interactions with personality and interests. While knowledge structures are evident in children and adolescents as a result of varied hobbies and extracurricular activities, individual differences in knowledge structures become increasingly apparent in early adulthood, as individuals are able to focus on more specialized topic areas in their academic, work, and extracurricular experiences. In addition, Ackerman (1996) stated that "interests and abilities jointly determine the orientation and success of individuals in these wide-ranging knowledge domains" (p. 245).

To further evaluate the importance of knowledge structures on adult intellectual development, a series of studies assessed a wide range of knowledge domains including a variety of academic topics (Ackerman & Rolfhus, 1999), health knowledge (Beier & Ackerman, 2003), and current events knowledge (Beier & Ackerman, 2001). Results showed that while older adults performed worse than younger adults in tests of numerical and spatial ability (i.e., tests of Gf), they consistently outperformed the younger adults in tests of verbal ability and domain knowledge (i.e., tests of Gc).

In these studies, there was little focus on the influence of life experiences in predicting domain knowledge. Results from these studies provide evidence that knowledge that is attributed to occupational or avocational experiences increases as a function of age. While middle-aged adults typically outperform younger adults in tests of domain knowledge, there is little research to demonstrate the relationship between

experience and domain knowledge. In one study, Beier & Ackerman (2003) found that education was significantly positively correlated with a domain knowledge test; however, no other studies have evaluated the influence of life experiences on domain knowledge. Accounting for individual differences in experience may lead to differential results on tests of domain knowledge, regardless of age. Specifically, experience within a given domain may serve as a proxy for age, such that individuals with a higher degree of experience within a given domain would be expected to perform better on a domain knowledge test (within that same domain) than an individual with a lower level of experience. Given that biodata measures are designed to assess life experiences, I suggest that the use of biodata may provide significant predictive validity for domain knowledge.

CHAPTER 5

HYPOTHESES

Study Overview

The purpose of the current study was to develop a domain specific biodata measure and to use this measure to predict domain knowledge in a sample of adults. The domain of financial issues was selected for the current study because of its practical utility and real-world relevance. Also, it was assumed that there would be significant differences in knowledge for this topic (see Ackerman & Beier, under review).

Research Questions and Hypotheses

The effects of biodata on domain knowledge

As discussed in the Ecology model, individual differences in affective, cognitive, and conative traits influence the pattern of behavioral choices that develop over time (Mumford & Stokes, 1992). Affective traits will influence the directions in which an individual is oriented based on his/her interests and personality traits, while conative traits will influence the level of motivation that an individual has, in terms of persistence and intensity in a particular direction. Cognitive determinants will influence the development of behavioral choice patterns through the internal and external limitations that are imposed on individuals as a result of ability and aptitude thresholds. Mael (1991) suggested that individual differences in affective, cognitive, and conative traits affect prior behaviors. Thus, he predicted a causal path between these variables.

Adapting this model to domain knowledge, prior behaviors may have a direct influence on domain knowledge, such that affective, cognitive, and conative traits

influence prior behaviors, which in turn, influence domain knowledge. Specifically, the first hypothesis can be stated as follows:

Hypothesis 1: Past experience will partially mediate the relationship between affective, cognitive, and conative determinants of performance and domain knowledge.

A main focus of the current study surrounds whether there is a significant relationship between biodata and domain knowledge. Based on previous research which has found significant correlations between age and domain knowledge (e.g., Beier & Ackerman, 2003; Beier & Ackerman, 2001), and between experience and performance (e.g., Russell et al., 1990), it was predicted that past experience within the financial issues domain would be positively correlated with domain knowledge on the financial issues knowledge pretest. More precisely:

Hypothesis 2: Level of past experience within the domain will be positively correlated with level of domain knowledge on the pre-test.

Knowledge gained as a result of academic and work experiences is expected to differ from knowledge gained as a result of informal experiences with family and friends and through extracurricular activities. I predicted that experiences in academic and work environments would be more focused on detailed, factual knowledge, while experiences with family, friends, and extracurricular activities would be associated with real-world, practical knowledge. In the current study, participants completed a battery of objective multiple choice questions as well as a set of open-ended scenarios requiring the participants to provide solutions for a set of problems related to a particular domain. Because the multiple choice questions focused on declarative knowledge, individuals who attributed the majority of their financial knowledge to academic and work

experiences were expected to perform better on this test than individuals who attributed the majority of their financial knowledge to extracurricular or at-home experiences. In contrast, the scenario tests focused on contextual knowledge in that they required participants to provide solutions for real-world financial situations. Thus, individuals who attributed their financial knowledge to extracurricular and at-home experiences were expected to perform better on this test than individuals with more academic or work experience.

Hypothesis 3: Attribution of experience will influence the type of knowledge assessment on which the individual has a greater chance of success.

3a. Individuals who relate the majority of their domain knowledge to extracurricular or at-home experiences will be more successful on the open-ended scenario test than individuals who relate the majority of their domain knowledge to educational or work experiences.

3b. Individuals who relate the majority of their domain knowledge to educational or work experiences will be more successful on the multiple-choice test than individuals who relate the majority of their domain knowledge to extracurricular or at-home experiences.

CHAPTER 6

METHOD

This research is part of a larger study of financial planning learning (see Ackerman & Beier, under review). The unique aspect of this proposal relates to the biodata measure.

Participants

“One hundred and forty-two adults were recruited through an advertisement in the Atlanta Journal-Constitution, a local mainstream daily newspaper or through referrals from other participants. The advertisement asked for participants interested in a ‘knowledge and learning study.’ Inclusion criteria were as follows: (1) Native English speaker, (2) normal, or corrected-to-normal vision, hearing and motor coordination, (3) some college education (which could include any college course enrollment), and (4) age between 18 and 69. Data from one participant were removed for failure to follow instructions. Age range of participants was 18 to 69, with a mean of 47.0 and a standard deviation of 13.2 years. Reported race/ethnicity was as follows: White (86, 61.0%), Black or African American (49, 34.8%), Asian (2, 1.4%), Unknown (4, 2.8%)” (Ackerman & Beier, under review). In addition, 65 participants were male (46.1%) and 76 participants were female (53.9%).

Apparatus

Questionnaire Packet

“The questionnaire packet included a variety of self-report measures designed to assess cognitive, affective, and conative traits that were relevant to both general aspects of individual differences in domain knowledge and the acquisition of new knowledge”

(Ackerman & Beier, under review). The biodata measure was included in this packet, along with some additional measures that are not reported here.

Personality

“Selected scales were administered from the International Personality Item Pool (IPIP Goldberg, 2005). Scales included: (1) Self-Discipline and Methodicalness, (2) Conservatism, (3) Extroversion, (4) need for Achievement, (5) Risk-taking, (6) Cautiousness, (7) Agreeableness, and (8) Neuroticism. Each scale was composed of 8-10 items that were balanced in terms of positive or negative statements. The response scale used was a six-point Likert-type scale, with explicit adjective references (1 = strongly disagree, 2 = moderately disagree, 3 = slightly disagree, 4 = slightly agree, 5 = moderately agree, and 6 = strongly agree).

Motivational Traits

The short-form of the Motivational Trait Questionnaire (Kanfer & Ackerman, 2000; see also Heggstad & Kanfer, 1999; Kanfer & Heggstad, 1997) is a Likert-type 48-item questionnaire that contains six scales. The scales represent markers for three underlying motivational trait factors: (1) Approach-oriented motivation (Desire to Learn, Mastery); (2) Competitive Excellence (Other-referenced goals, Competitiveness), and (3) Aversion-related motivational traits (Worry, Emotionality)” (Ackerman & Beier, under review).

Biodata

The biodata measure was presented in two parts. In the first part, a set of four items was used to determine the degree to which an individual’s financial knowledge was attributable to a particular source (e.g., Work, Academic, Extracurricular, or At-

Home experiences). In the second part, a 55-item biodata measure provided a series of statements about financial-related behaviors and experiences (e.g., “I listen to or watch the financial news” or “I meet with an accountant or money manager.”) Response options were presented in a 6-point Likert-type scale (from 1=very untrue of me to 6= very true of me).

In creating a biodata measure, Russell (1994) suggested shifting the role of subject matter expert to individuals who are more likely to have experienced the construct of interest and to use life history interviews to target aspects of their lives that they feel were integral in enhancing their knowledge of the domain. Consistent with this argument, two experienced-laypeople within the financial domain were interviewed using a standard set of guiding questions for each interview. The information obtained from these interviews was used to rationally develop items for this measure. The biodata measure was administered in a pilot study with undergraduate students. Items were revised as necessary.

Ability Test Battery

“The ability battery included ten tests designed to provide assessments of Gf and Gc. Five tests were included to assess Gf: (1) Number Series (a test of inductive reasoning from the Primary Mental Abilities battery; Thurstone, 1962); (2) Spatial Analogies (an analogical reasoning test created by P. Nichols; see Ackerman & Kanfer, 1993); (3) Math Approximation (a test of estimated math problem solving, see Ackerman, Beier, & Bowen, 2002; modeled after a test described in Guilford & Lacey, 1947); (4) Diagramming Relations (a test of logical reasoning; Educational Testing Service [ETS] Kit, Ekstrom, French, Harman, & Dermen, 1976; and (5) Word Problem

Solving (a test of math/inductive reasoning created by D. Lohman; see Ackerman & Kanfer, 1993).

Five tests were included to assess Gc: (1) Multidimensional Aptitude Battery (MAB) Comprehension (a test of cultural knowledge; Jackson, 1985); (2) MAB Similarities (a test of verbal knowledge; Jackson, 1985); (3) Wechsler Adult Intelligence Scales-Revised (WAIS-R; Wechsler, 1981) Information Test (a test of general knowledge); (4) Cloze (a test of word fluency and verbal comprehension; see Ackerman, Beier, & Bowen, 2001); and (5) Extended Range Vocabulary (a multiple-choice vocabulary test, Educational Testing Service [ETS] Kit, Ekstrom, et al., 1976).

Five of the tests (WAIS-R Information, Word Problem Solving, Vocabulary, Math Approximation, and Cloze) were administered with a paper and pencil format, with prerecorded instructions presented over a public address system. The remaining tests were administered on PC-type computers, with instructions presented over headphones, and single items appearing sequentially on the screen. Time limits were imposed on both types of testing formats.

Financial Issues Pretest Knowledge Assessment

The pretest of financial issues had two components, a multiple choice test and an open-ended scenario test. Each are described below.

Financial Issues Multiple Choice Test

This test had 74 items. The items covered topics that included basic financial issues concepts, such as liability, compounded interest, types of securities, dividends, and a variety of financial planning topics, such as Individual Retirement Accounts (IRAs),

401(k) plans, health insurance, life insurance, taxes, educational savings accounts, divorce-related financial issues. Time allowed for completion of the test was 24 minutes.

Financial Issues Open-Ended Scenario Test

This test had six open-ended items. Each item provided a short narrative about two paragraphs in length that described an individual or a couple's financial situation and some additional demographic background. Each item was also accompanied by a table that provided a breakdown of financial assets and liabilities for that scenario (e.g., ages, salary, home mortgage and equity, retirement accounts, pensions, investments, car payments, tuition payments, loans and credit card debt). Each item posed a question related to the scenario (e.g., "how would you advise the individual to begin saving for retirement," or "how would you advise the couple to plan for accumulating the funds necessary for the college education expenses of their child"). The participants were instructed that they were to focus their answers on concepts and not on specific calculations. Time allowed for completion of this test was 45 minutes.

Financial Issues Self-study materials

The self-study materials included two components: a folder containing reading materials, and a binder/Compact Disc (CD).

Reading Materials

The articles were gathered from the World Wide Web and from books on financial planning. There were 20 articles, from 2-16 pages in length. The articles were selected to range from very basic information to a somewhat more advanced treatment of the various financial planning concepts and issues. However, all of the articles selected

were sufficiently basic to not require prior knowledge of financial planning in order to understand the materials. Instructions included in the folder indicated that the participant should not write directly on the articles, but on included lined pages for notes. The instructions reminded the participants that there would be a test on the topic at the next laboratory session.

Binder/CD Materials

The binder contained the following items: (1) printed instructions, (2) audio CD, (3) printed materials, and (4) lined notes pages. The printed instructions described the materials in the binder, and provided directions for the use of the audio CD in conjunction with the printed materials (e.g., a tone was sounded on the CD to indicate to the participants when the next page of the printed materials was to be selected). Participants were also instructed that they could pause the CD at any time, replay or stop segments, or read the printed materials without listening to the CD. The printed/audio materials were composed of 5 segments: (1) General investment information, (2) Managing money, (3) College planning, (4) Retirement planning, and (5) Protection planning. Each segment has approximately a dozen PowerPoint “slides” that were linked to a 10-15 min. audio narration. Total time of the audio narration was 66 min.

Post Self-study questionnaire

A short questionnaire was administered that asked the participants how much time they spent in reading the printed materials and reviewing the binder/CD materials, along with several questions that pertained to any self-generated search of additional materials on financial issues. Ten min was allowed for completion of this questionnaire.

Financial Issues Posttest Knowledge Assessment

Similar to the Financial Planning pretest knowledge assessment, there were both multiple choice and open-ended scenario tests. The multiple-choice posttest was identical in content to the pretest, but with a reordering of items. The open-ended scenario test was a parallel test to the pretest. That is, each of the pretest items was matched in general content to the posttest, but minor details were altered to render the items more novel in appearance, and discourage the role of memory in item responses. To distribute any item-specific variance across the pretests and posttests, counterbalancing was employed such that half of the participants received the pretests as posttests and half of the participants received the posttests as pretests, with random assignment to order conditions.

Procedure

The study had four components. After enrollment in the study (over the telephone), the instructions, consent form, and questionnaire packet were mailed to the participant up to two weeks prior to the first scheduled laboratory session. The participants were instructed to complete the questionnaire packet in a quiet place at home, and to bring the completed questionnaire to the first laboratory session. The first laboratory session included 5 paper and pencil ability tests, followed by a break, and then 5 ability tests administered on the computer. After a second 5 min break, the participants completed both the multiple choice and open-ended scenario financial planning pretest scales. Participants were allowed 25 minutes for the multiple-choice scale, and 45 min for the scenario scales. At the conclusion of the first laboratory session, the self-study materials were distributed to the participants, and portable compact disc (CD) players were checked out to those participants who did not have access to a CD player. One week

after the first laboratory session, the participants returned for the second laboratory session. The post self-study questionnaire was completed first, followed by the multiple choice financial planning posttest and the open-ended financial planning posttest—using paper and pencil and identical time limits to the first session” (Ackerman & Beier, 2005). After a 5 min break, participants completed computerized knowledge tests for current events and for technology domains (Ackerman & Beier, 2005; see also Beier & Ackerman, 2001). At the completion of these tests, participants were debriefed and compensated \$100 each for their participation.

CHAPTER 7

RESULTS

Overview

The analysis plan consisted of two stages which were used to determine whether a biodata measure could be used in the prediction of domain knowledge. First, the 55-item biodata measure was organized into scales and the reliability of the scales was determined. Second, specific tests of the hypotheses were performed. Preliminary correlations are reported between the biodata measure and the financial issues knowledge tests, and between the biodata measure and the ability and non-ability traits. Initially, the proposed model was entered into a path analysis to evaluate the causal influence of biodata on domain knowledge. Next, the biodata measure was entered into a series of hierarchical multiple regressions to evaluate the predictive validity for Financial Planning knowledge in isolation, and the incremental predictive validity of the biodata measure over and above the ability and non-ability traits. Finally, tests of mediation were conducted to determine whether the biodata measure partially explained the relationship between the ability and non-ability traits and domain knowledge; providing specific information on the relationship between individual trait measures, biodata, and domain knowledge.

Reliability Analysis

The biodata items in the measure were initially constructed to cover 5 categories of financial issues: General Investment (19 items), Money Management (21 items), Retirement Planning (5 items), Protection Planning (6 items), and College Planning (4 items). The internal consistency reliability was determined for these 5 scales: General

Investment ($\alpha = .90$), Money Management ($\alpha = .71$), Retirement Planning ($\alpha = .44$), Protection Planning ($\alpha = .37$), and College Planning ($\alpha = .37$). Nunnally (1978) recommended that Cronbach's alpha be at least .70 for a set of items considered to be a scale. Although low alpha levels are not inherently problematic for biodata items, I decided to revise the scales because it did not seem appropriate to use these scales to draw conclusions about the relationship between biodata and knowledge.

In revising the biodata scales, the General Investment scale was kept intact. The remaining 36 items were entered into an exploratory factor analysis for further evaluation. Based on multiple factor solutions and rational analysis of each of the solutions, a second factor emerged, which I identified as Fiscal Responsibility. This 18-item scale includes some of the items that were in the original Money Management scale, but also includes some items from the other three original scales (Retirement Planning, Protection Planning, and College Planning), such as: "When starting a new job, I educate myself about the benefits provided by my employer (for example, health insurance, life insurance)." The remaining items were rationally combined into a third scale, which I identified as Financial-related Life Events. This 11-item scale includes items from all 4 original scales (Money Management, Retirement Planning, Protection Planning, and College Planning). The 7 remaining items on the measure were not included within a scale. The alpha values (shown in Table 1) for the revised scales were somewhat better than those for the original scales: General Investment ($\alpha=.90$), Fiscal Responsibility ($\alpha=.83$), Financial-related Life Events ($\alpha=.60$). The alpha values for two of the three scales were greater than .80, the cutoff value that Nunnally (1978) considers to be

“optimal.” The Financial-related Life Events scale may have a lower alpha value due to the multidimensional nature of the items within this scale.

Table 1
Intercorrelations and Cronbach’s alpha for biodata scales

Biodata scales	1	2	3	α
1. General Investment				.90
2. Fiscal Responsibility	.71*			.83
3. Life Events	.10	.05	—	.60

*p<.05

Correlations

Knowledge and Biodata Correlations

Correlations between the biodata scales and Financial Planning knowledge tests (Multiple Choice, Scenarios, and Composite Pretest) are shown in Table 2.

Table 2
Correlations between biodata scales and knowledge tests.

Biodata Scales	Knowledge Tests		
	Financial Planning Multiple Choice	Financial Planning Open Ended Scenarios	Financial Planning Composite Pretest
General Investment	.49*	.37*	.48*
Fiscal Responsibility	.46*	.45*	.50*
Life Events	.04	.10	.08

*p<.05

For the General Investment and Fiscal Responsibility scales, correlations with the domain knowledge tests were substantial and significant, lending preliminary support to the prediction that level of past experience within the domain would be positively correlated with level of domain knowledge on the pretest (Hypothesis #2). However, the correlations between the Financial-related Life Events scale and the Financial Planning knowledge tests were not significant.

Ability-Biodata correlations

The correlations between fluid intelligence (Gf), crystallized intelligence (Gc), and the biodata scales are shown in Table 3.

Table 3
Correlations between Ability/ Non-Ability and Biodata

Ability/ Non-Ability traits	Biodata Scales		
	General Investment	Fiscal Responsibility	Financial-related Life Events
Gf	.23*	.16	-.25*
Gc	.13	.13	-.09
Extraversion	.17*	.20*	.15
Neuroticism	.23**	.28**	.18*
need for Achievement	.17*	.35**	.08
Agreeableness	-.11	.02	.16
Self Discipline	.10	.28**	.03
Risk	-.001	-.19*	.18*
Conservatism	.04	.14	.04
Cautiousness	.04	.18*	-.07
Desire to Learn	.11	.17*	.16
Mastery	.24**	.33**	.06
Other-referenced goals	.31**	.23**	-.19*
Competitiveness	.34**	.23**	-.15
Worry	-.16	-.09	-.21*
Emotionality	-.12	-.15	-.09

*p<.05; **p<.01; Gf= Fluid intelligence; Gc= Crystallized intelligence

The General Investment biodata scale was significantly, positively correlated with Gf ($r=.23, p<.05$), while the Financial-related Life Events biodata scale was significantly, negatively correlated with Gf ($r=-.25, p<.05$). Correlations between the biodata scales and Gc were not significant.

Non-Ability and Biodata Correlations

The General Investment biodata scale is significantly, positively correlated with three scales on the MTQ. Specifically, Mastery ($r=.24, p<.01$), Other-referenced goals ($r=.31, p<.01$), and Competitiveness ($r=.34, p<.01$), as well as need for Achievement ($r=.17, p<.05$). Since this biodata scale includes questions about setting aside money to invest and researching various types of investments, it seems appropriate that this scale would tap the conative determinants of performance, such as competitiveness and achievement orientation. The Fiscal Responsibility biodata scale combines items that focus on personal responsibility and preparedness. As such, this scale was significantly correlated with personality traits such as self-discipline ($r=.28, p<.01$) and need for Achievement ($r=.35, p<.01$), and was negatively correlated with risk-taking ($r=-.19, p<.05$). In addition, all three biodata scales (i.e., General Investment, Fiscal Responsibility, and Financial-related Life Events) were significantly correlated with Neuroticism ($r = .23, .28, .35, p < .01$). The neuroticism scale is reverse scored, so a positive correlation with the biodata scale implies that life experiences in the current measure are negatively related to neuroticism. The Fiscal Responsibility scale is significantly correlated with the approach-oriented scales of the MTQ: Desire to Learn ($r=.17, p<.05$), Mastery ($r=.33, p<.01$), Other-referenced goals ($r=.23, p<.01$), and Competitiveness ($r=.23, p<.01$).

The Financial-related Life Events scale was significantly correlated with risk-taking ($r=.18, p<.05$), such that people who are more likely to take risks may be more likely to have experienced the negative life events (e.g., unemployment, divorce) that are measured in the biodata scale.

In evaluating whether the context of experience differentially affected performance on the knowledge tests (in terms of the multiple choice test versus the scenario test), it was found that Academic-oriented experience was significantly different than Extracurricular-based experience as a predictor of success on the Financial Planning multiple choice knowledge test ($t(138)=2.79, p<.05$). In addition, it was found that Academic-oriented experience was significantly different than Home-based experience as a predictor of success on the Financial Planning multiple choice knowledge test ($t(138)=2.30, p<.05$), lending partial support to the prediction that attribution of experience would influence the type of knowledge assessment on which the individual was most successful (Hypothesis #3). Bivariate correlations between context of experience and domain knowledge are shown in Table 4.

Table 4
Correlations between context of experience and knowledge.

	1	2	3	4	5	6
1. Work experience						
2. Academic experience	.54*					
3. Extracurricular experience	.27*	.44*				
4. Home experience	.22*	.23*	.41*			
5. Financial Planning Multiple Choice	.03	.18*	-.07	-.06		
6. Financial Planning Open-Ended Scenarios	.07	.10	.05	.08	.63*	
7. Financial Planning Composite Pretest	.06	.16	-.01	.01	.90*	.90*

* $p<.05$

Academic experience was the only context that was significantly correlated with domain knowledge ($r=.18, p<.05$ with Financial Planning Multiple Choice). Extracurricular and At-Home experiences were negatively correlated with Financial Planning Multiple Choice and positively correlated with the Financial Planning Scenario test as hypothesized; however, these correlations were not significant.

Path Analysis

In the hypothesized model, it was proposed that the biodata measure would mediate the relationship between the ability and non-ability traits and domain knowledge. The hypothesis that past experience would partially mediate the relationship between affective, cognitive, and conative determinants of performance and domain knowledge (Hypothesis #1) was tested with both Structural Equation Modeling techniques in LISREL (Jöreskog & Sörbom, 1993) and Baron and Kenny's (1986) approach to mediation. Based on recommendations from Hu & Bentler (1999), a cutoff value close to .95 for the Comparative Fit Index (CFI) and a cutoff value close to .06 for Root Mean Squared Error of Approximation (RMSEA) are needed to conclude that there is a relatively good fit to the data. In addition, Bentler (1990) suggested that a CFI between .90 and .95 represents acceptable fit to the data. A CFI greater than .95 is indicative of a good fit to the data. MacCallum et al. (1996) recommend the following criteria for the RMSEA values: $RMSEA \leq .05$ represents a "close fit"; .05-.08 is a "fair" fit; .08-.10 is "mediocre"; and $RMSEA > .10$ represents a "poor" fit to the data. These general recommendations of fit terminology will be used in drawing conclusions about the hypothesized and alternate models.

Initially, the ability and non-ability variables were entered into separate path models. In the original *ability* model, Gf and Gc were set to predict biodata (measured as the latent construct with the three biodata scales as the manifest indicators), with the biodata measure predicting domain knowledge. Consistent with theoretical expectation (e.g., Ackerman & Beier, under review), a direct path was placed in the model, leading from Gc to domain knowledge. This model is shown in Figure 2.

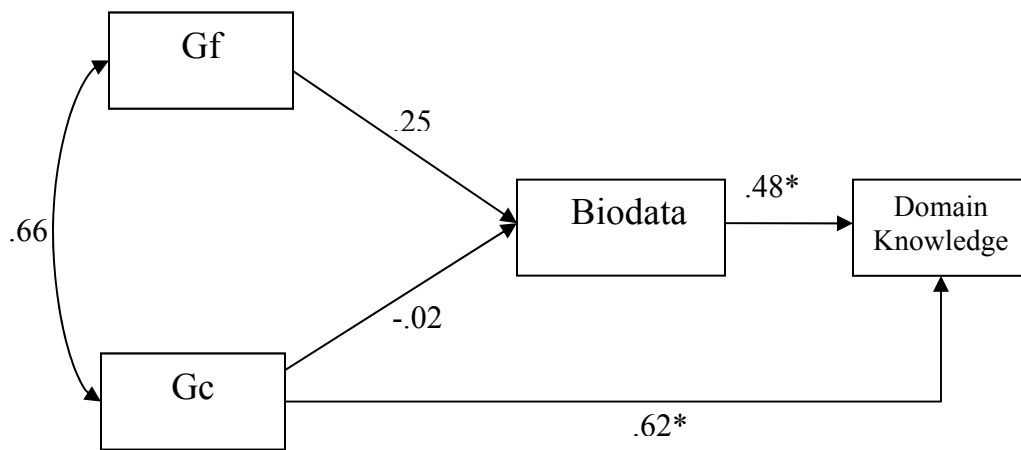


Figure 2. Path model for predicting financial issues domain knowledge pretest performance with ability traits and biodata.

The fit of the original *ability* model was acceptable, $\chi^2(85, N=141) = 200.14, p < .01$, RMSEA = .10, CFI = .90.

In the original *non-ability* model, 14 non-ability traits were used to predict the biodata measure, which in turn was set to predict domain knowledge. In this model, shown in Figure 3, non-significant paths have been dropped for the sake of clarity. The fit of the model was good, $\chi^2(60, N=141) = 83.64, p < .05$, RMSEA = .048, CFI = .98.

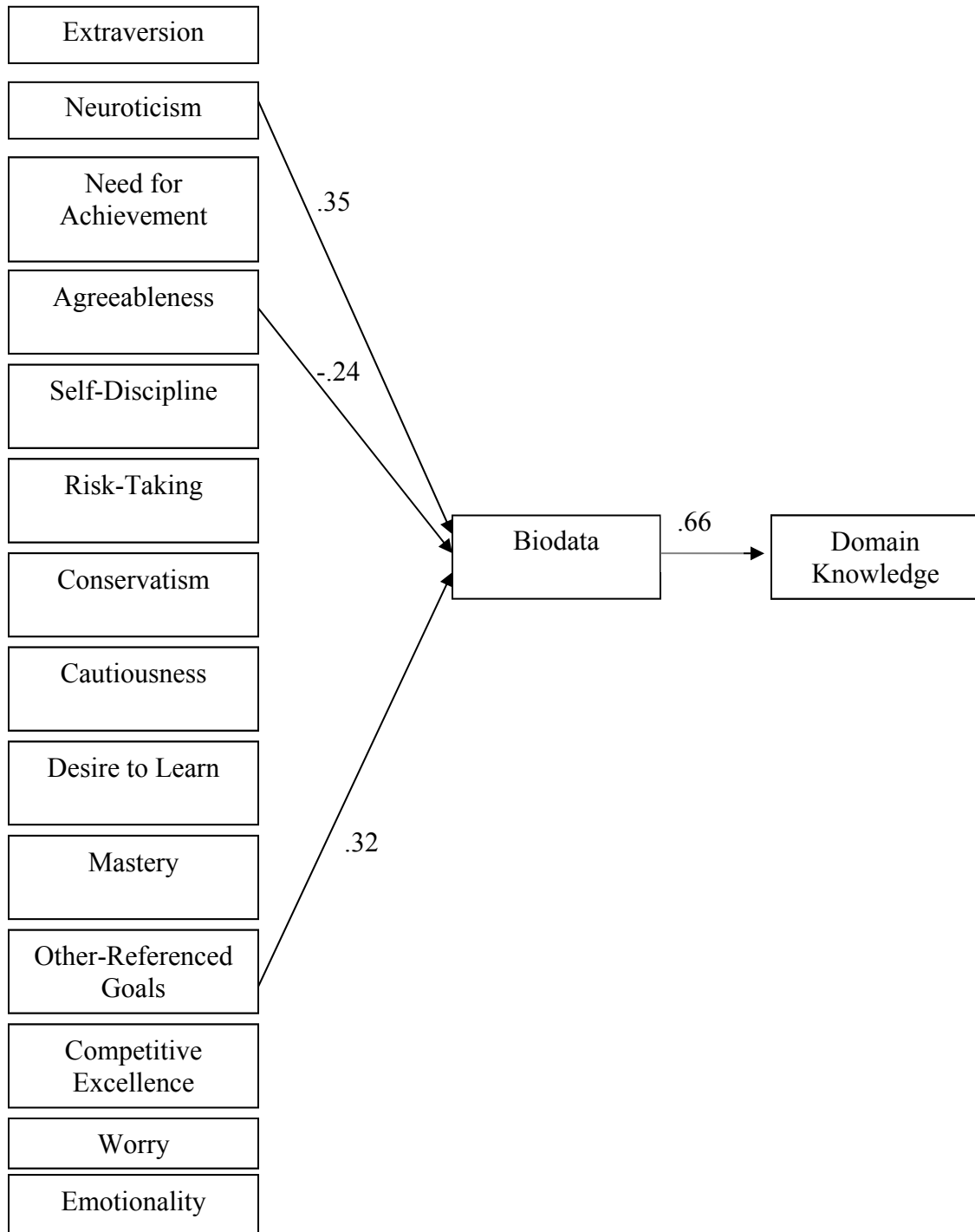


Figure 3. Path model for predicting financial issues domain knowledge pretest performance with non-ability traits and biodata.

Alternate models were tested using trait complexes (e.g., see Ackerman, 1996, 1997; Ackerman & Heggestad, 1997), to determine if the use of trait complexes, rather than individual non-ability measures, might better predict biodata and domain knowledge. The use of trait complexes is based on meta-analyses of personality, interest, and ability relations that have shown that there is considerable overlap among many of these measures. In the first alternate model (Figure 4), five trait complexes (math/science/financial, achievement/ learning orientation, anxiety/performance orientation, social/enterprising, and verbal/intellectual) were used to predict biodata, which in turn was used to predict domain knowledge.

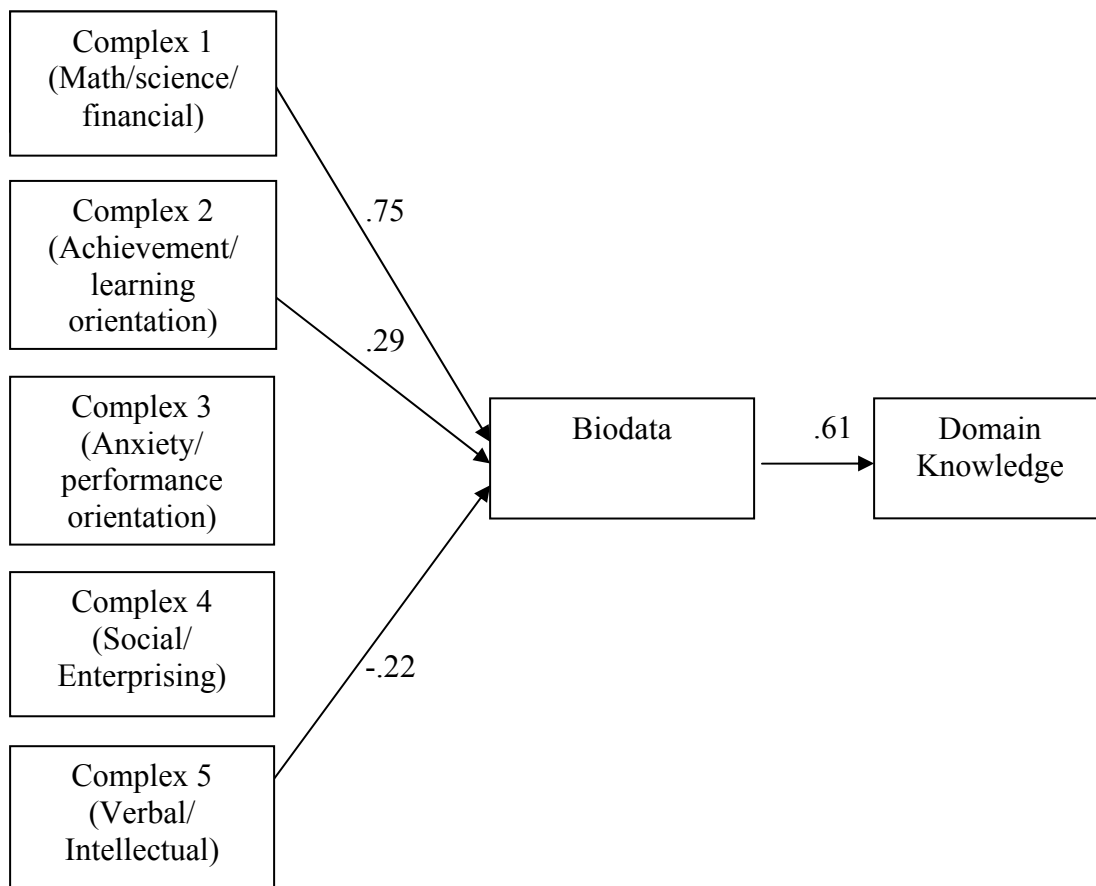


Figure 4. Path model for predicting financial issues domain knowledge pretest performance with trait complexes and biodata.

This model had a poor fit to the data, $\chi^2 = (613, N=141) = 1806.96, p < .01, RMSEA = .12, CFI = .58$. In this model, non-significant paths have been dropped for the sake of clarity.

In the second alternate model, Gf, Gc, and the trait complexes were entered into the model simultaneously. In this model, shown in Figure 5, non-significant paths have been dropped.

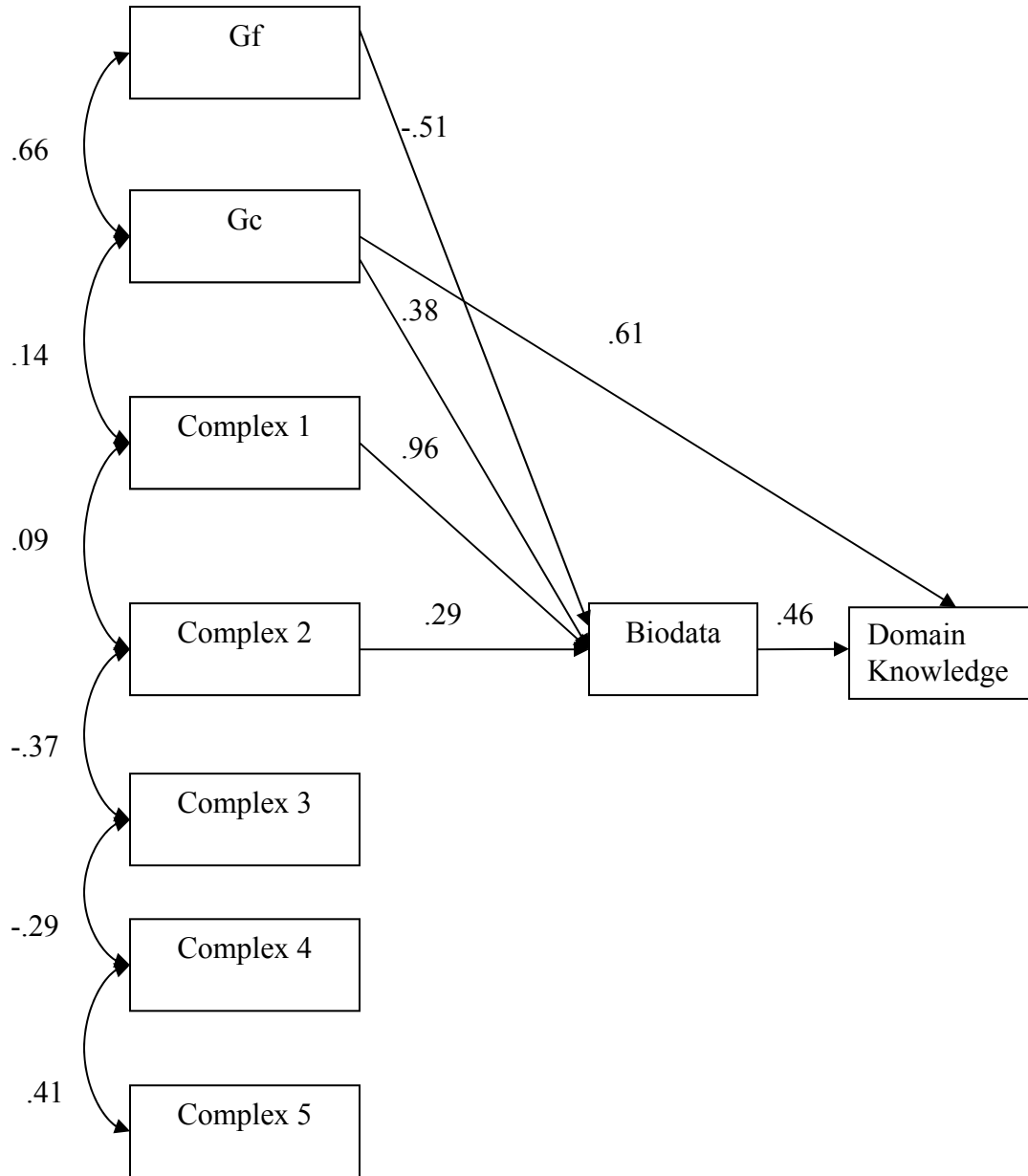


Figure 5. Path model for predicting financial issues knowledge with ability traits, trait complexes and biodata.

Although the fit for this model was poor, $\chi^2 = (1004, N=141) = 2511.54, p < .01$, RMSEA = .10, CFI = .63, there was a significant relationship between Gf and Biodata, Gc and Biodata, Trait Complex 1 (math/science/financial) and biodata, and Trait Complex 2 (Achievement/ Learning Orientation) and biodata.

In the third alternate model, the biodata was removed from the *ability* model to confirm that inclusion of the biodata measure did, in fact, lead to a better fitting model (Figure 6).

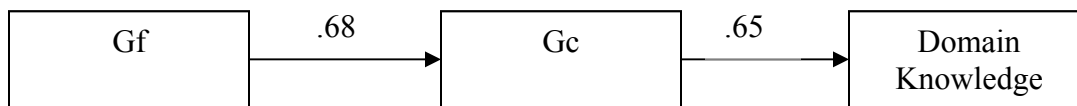


Figure 6. Path model for predicting financial issues domain knowledge pretest performance with ability traits.

Although this model had acceptable fit based on the CFI value, $\chi^2 = (52, N=141) = 154.73, p < .01$, RMSEA = .12, CFI = .90, the fit was slightly improved by including the biodata (see Figure 2). This same effect was not found when the biodata measure was removed from the *non-ability* model (see Figure 7; non-significant paths have been dropped). This actually led to a better fitting model, $\chi^2 = (13, N=141) = 11.25, p = .59$, RMSEA = .00, CFI = 1.00 than the original non-ability model with the biodata included (see Figure 2).

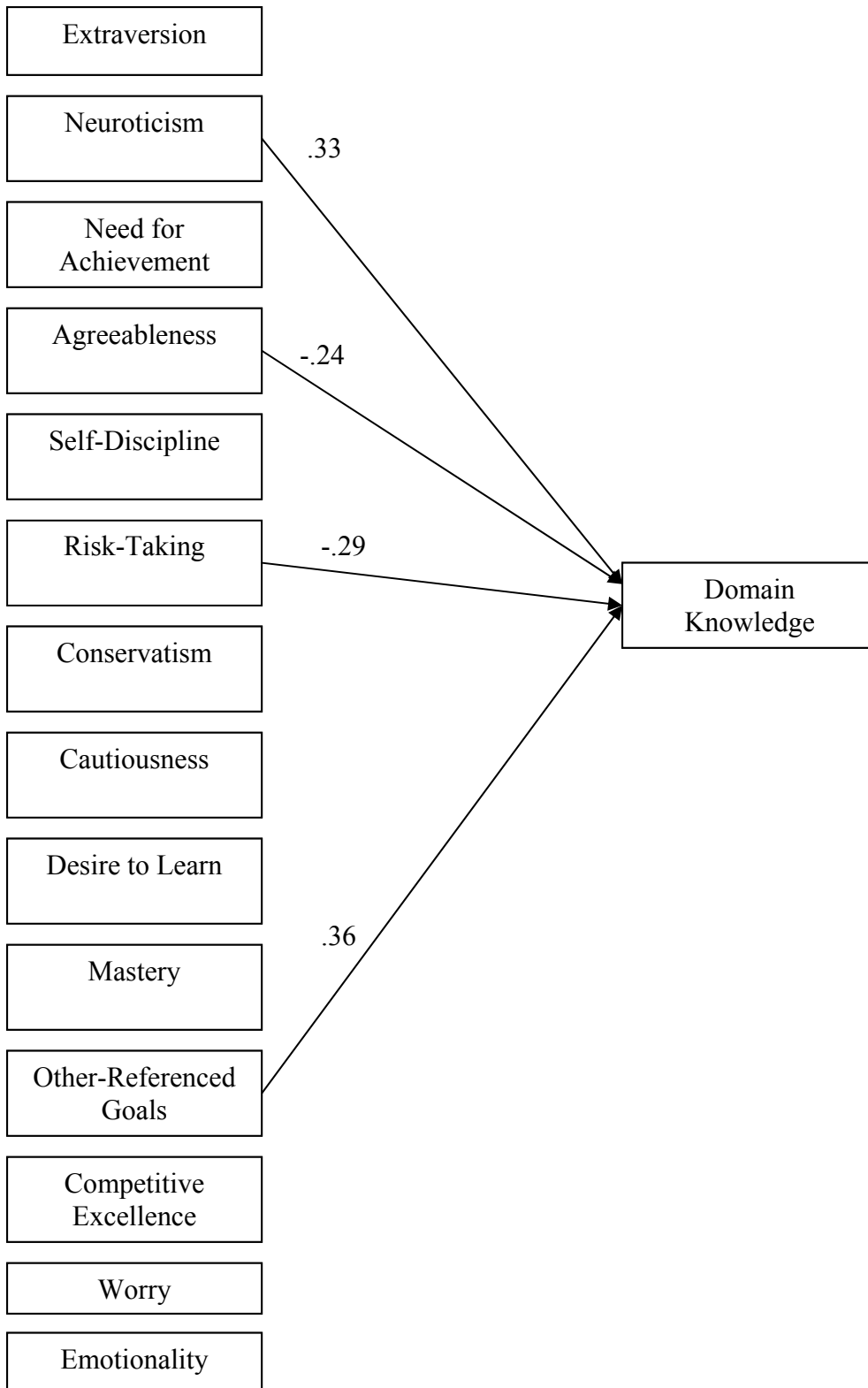


Figure 7. Path model for predicting financial issues domain knowledge pretest performance with non-ability traits.

In a subsequent analysis, context of experience (e.g., Work, Academic, Extracurricular, and Home-based experience) and the domain knowledge tests (i.e., Multiple Choice and Scenario) were entered into a path analysis to determine whether the context of experience influenced the type of knowledge assessment on which an individual was most successful. A baseline model included all possible relationships between context of experience and domain knowledge (Figure 8).

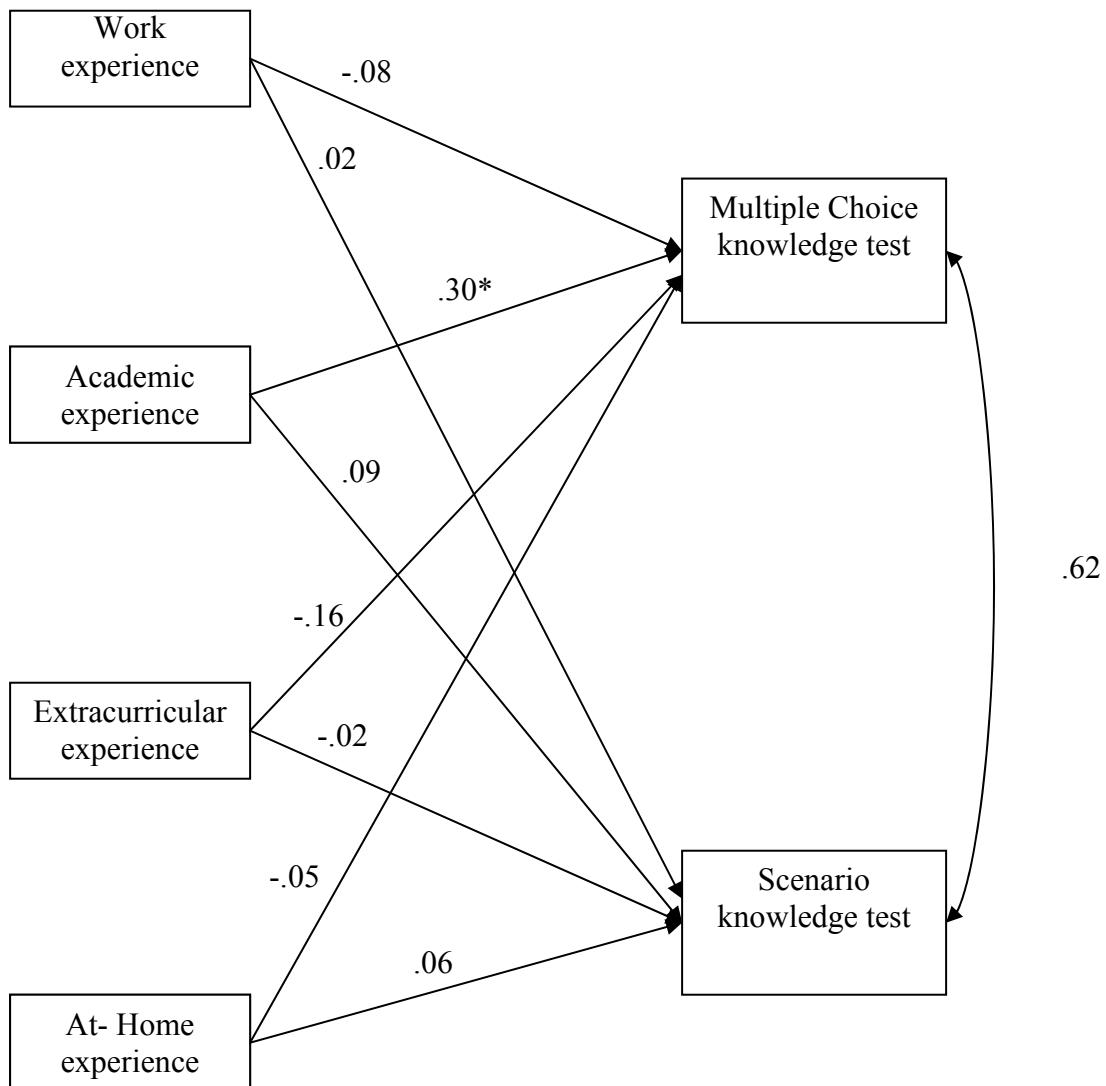


Figure 8. Path model for predicting financial issues pretest performance on the scenario and multiple choice tests.

This was a saturated model, and thus could not be tested. The hypothesized model proposed that Work and Academic experience would predict domain knowledge as measured by the multiple choice test, while Extracurricular and At-Home experience would predict domain knowledge as measured by the scenario test (Figure 9).

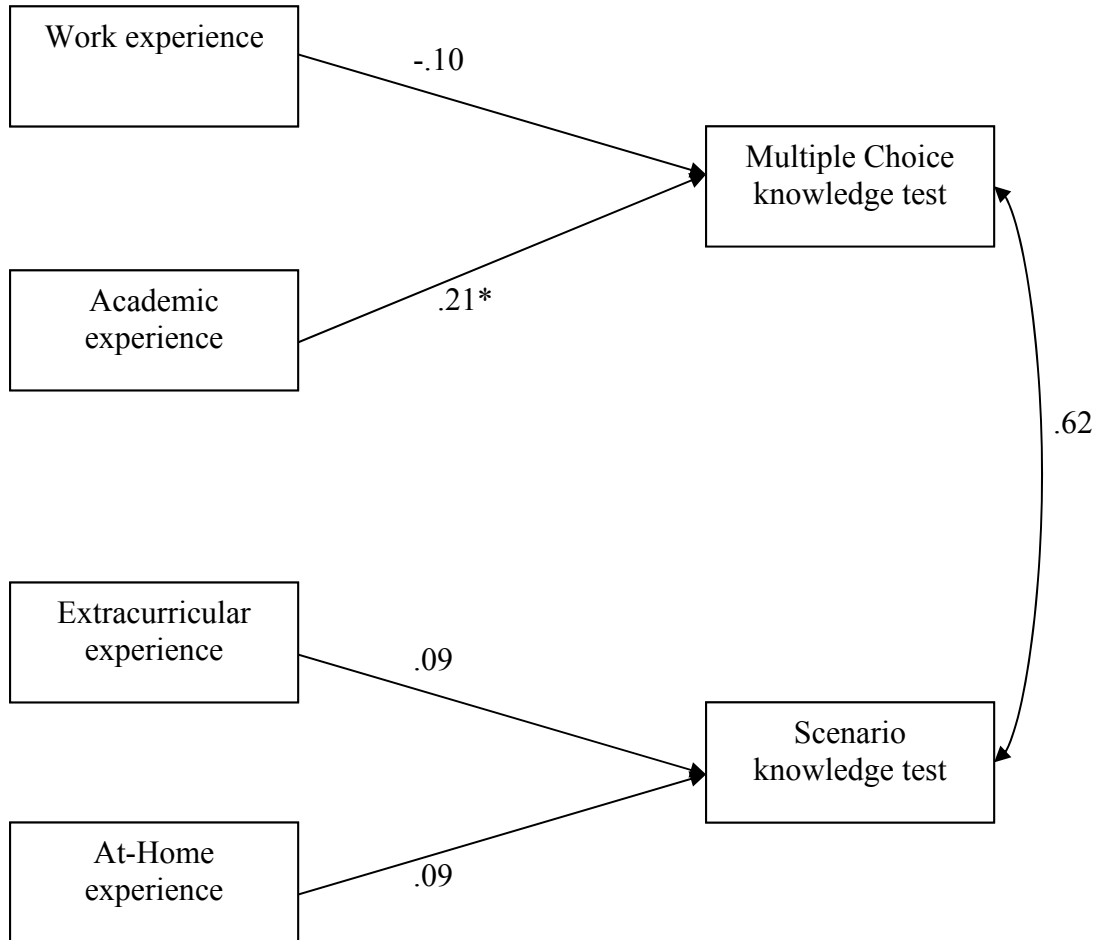


Figure 9. Hypothesized path model for predicting financial issues pretest performance on the scenario and multiple choice tests.

This model had good fit, $\chi^2(3, N=141) = 4.19, p = .24, RMSEA = .05, CFI = .99$;

however, the path between Academic experience and the multiple choice test of domain knowledge was the only significant path. This finding provides partial support for the prediction that Academic experiences would be significantly related to success on the

multiple choice knowledge test (Hypothesis #3). In future research, more conclusive results may be obtained with a more extensive measure about the context of experience. In the current study, this was measured with only a single item for each context.

Multiple Regression Prediction of Knowledge

Hierarchical multiple regression procedures allow for an examination of the overall predictive validity of the biodata measure for pretest knowledge, over and above that offered by the ability and non-ability measures. In addition to the hierarchical regressions, the multiple correlations between the predictor variables (in isolation) and the criterion variables are also provided. Two sets of regressions were completed. The first set evaluated the predictive validity of the biodata measure over and above ability and the trait complexes. Results for these analyses are shown in Table 5. The second set of regressions evaluated the predictive validity of the biodata measure over and above ability (Gf, Gc) and the various non-ability traits from which the trait complexes are composed. Results for these analyses are shown in Table 6.

Table 5

Summary of multiple correlations for predicting financial planning knowledge scores, using trait complexes.

		Step 1	Step 2	Step 3	Step 4
		Gf	Gc	Trait Complexes	Biodata
Financial Planning Multiple Choice	R ² in isolation	.23**	.43**	.30**	.27**
	R ² to add	.23**	.21**	.14**	.08**
	Total R ²	.23**	.44**	.58**	.66**
Financial Planning Open Ended Scenarios	R ² in isolation	.06**	.13**	.10*	.21**
	R ² to add	.06**	.08**	.07*	.13**
	Total R ²	.06**	.13**	.21*	.34**
Financial Planning Composite Pretest	R ² in isolation	.16**	.32**	.21**	.28**
	R ² to add	.16**	.17**	.11**	.13**
	Total R ²	.16**	.32**	.44**	.56**

Notes: ns=not significant; *p<.05; **p<.01; N=141. Step 1 and 2 are single degree of freedom each in the numerator, Step 3 is 5 degrees of freedom, and Step 4 is 3 degrees of freedom. Step 1 is 139 degrees of freedom in the denominator, Step 2 is 138 degrees of freedom, Step 3 is 133 degrees of freedom, and Step 4 is 130 degrees of freedom.

Table 6

Summary of multiple correlations for predicting financial planning knowledge scores

		Step 1	Step 2	Step 3	Step 4
		Gf	Gc	Non-Ability	Biodata
Financial Planning Multiple Choice	R ² in isolation	.23**	.43**	.52**	.27**
	R ² to add	.23**	.21**	.25**	.05**
	Total R ²	.23**	.44**	.69**	.74**
Financial Planning Open Ended Scenarios	R ² in isolation	.06**	.13**	.36*	.21**
	R ² to add	.06**	.08**	.27ns	.10**
	Total R ²	.06**	.13**	.40ns	.50**
Financial Planning Composite Pretest	R ² in isolation	.16**	.32**	.48**	.28**
	R ² to add	.16**	.17**	.27**	.08**
	Total R ²	.16**	.32**	.59**	.67**

Notes: ns=not significant; *p<.05; **p<.01; N=141. Step 1 and 2 are single degree of freedom each in the numerator, Step 3 is 33 degrees of freedom, and Step 4 is 3 degrees of freedom. Step 1 is 139 degrees of freedom in the denominator, Step 2 is 138 degrees of freedom, Step 3 is 105 degrees of freedom, and Step 4 is 102 degrees of freedom.

For Financial Planning Multiple Choice knowledge, biodata accounted for 8.1% of the variance in pre-test performance over and above Gf, Gc, and the trait complexes. The inclusion of ability, the trait complexes, and biodata for the prediction of financial issues multiple choice knowledge accounted for 65.9% of the variance in pre-test performance on the multiple choice knowledge test. For Financial Planning Scenario knowledge, biodata accounted for 13.1% of the variance in pre-test performance over and above Gf, Gc, and the trait complexes. In total, Gf, Gc, the trait complexes, and biodata accounted for 33.6% of the variance in pre-test performance on the scenario test.

The second set of regression analyses shows the variance accounted for by the biodata measure over and above the ability and non-ability traits. For Financial Planning Multiple Choice knowledge, biodata accounted for 4.6% of the variance over and above Gf, Gc, and the various non-ability traits. In total, Gf, Gc, the non-ability measures, and biodata accounted for 73.8% of the variance in pre-test performance on the scenario test. For the Financial Planning Scenario test, biodata accounted for 9.8% of the variance over and above the ability and non-ability traits. Inclusion of all traits for prediction of Financial Planning scenario knowledge accounted for 49.7% of the variance in pre-test performance. The results of these multiple regressions lend additional support to Hypothesis 1, in that inclusion of the biodata measure had incremental predictive validity for domain knowledge over and above that obtained with ability and non-ability traits alone.

In an alternate regression analysis, the biodata items were entered into a stepwise regression procedure. The results are shown in Tables 7-9.

Table 7

Stepwise Regression of biodata items on Financial Planning Multiple Choice

	Biodata Item	R ² in isolation	R ² to add	Total R ²
Step 1	“I have done my own research on aspects of financial planning, such as Roth IRAs.”	.29**	.30**	.29**
Step 2	“I have lost a significant amount of money in the stock market.”	.22**	.07**	.36**
Step 3	“I have worked for a company that sponsors retirement plans.”	.10**	.03**	.39**
Step 4	“I research ways to reduce debt.”	-.01	.03**	.42**
Step 5	“I follow trends related to the stock market.”	.24**	.03**	.44**
Step 6	“My parents stressed the importance of effective money management.”	.01	.02**	.46**
Step 7	“I have collected unemployment at some point.”	.01	.02*	.47*
Step 8	“I have canceled credit cards in the past.”	.11**	.02*	.49*

Notes: ns=not significant; *p<.05; **p<.01; N=141. Steps 1-6 are single degree of freedom each in the numerator.

Table 8

Stepwise Regression of biodata items on Financial Planning Open Ended Scenarios

	Biodata Item	R ² in isolation	R ² to add	Total R ²
Step 1	“I have done my own research on aspects of financial planning, such as Roth IRAs.”	.17**	.17**	.17**
Step 2	“I often pay more than the minimum balance on my credit cards.”	.15**	.07**	.23**
Step 3	“I followed the events surrounding Martha Stewart’s indictment.”	.06**	.05**	.27**
Step 4	“When starting a new job, I educate myself about the benefits provided by my employer (for example, health insurance, life insurance).”	.10**	.04**	.31**
Step 5	“I have, or someone in my immediate family has, refinanced his/her home.”	.05**	.03*	.33*

Notes: ns=not significant; *p<.05; **p<.01; N=141. Steps 1-6 are single degree of freedom each in the numerator

Table 9
Stepwise Regression of biodata items on Financial Planning Composite Pretest

	Biodata Item	R ² in isolation	R ² to add	Total R ²
Step 1	“I have done my own research on aspects of financial planning, such as Roth IRAs.”	.28**	.28**	.28**
Step 2	“I have lost a significant amount of money in the stock market.”	.20**	.07**	.34**
Step 3	“I have, or someone in my immediate family has, refinanced his/her home.”	.05**	.04**	.38**
Step 4	“I often pay more than the minimum balance on my credit cards.”	.15**	.03*	.40*
Step 5	“I followed the events surrounding the Enron and WorldCom scandals”.	.17**	.02*	.41*
Step 6	“I research ways to reduce debt”.	.00	.02*	.43*

Notes: ns=not significant; *p<.05; **p<.01; N=14. Steps 1-6 are single degree of freedom each in the numerator.

The use of the stepwise regression is based on the notion that some items within a given measure (i.e., the biodata measure) may not have an important explanatory influence on the outcome variable (i.e., domain knowledge). Thus, the stepwise regression identified the individual biodata items that accounted for a statistically significant amount of the variance in domain knowledge. The stepwise regression of the biodata items on the Financial Planning Multiple Choice test showed that 49% of the variance in Financial Planning Multiple Choice knowledge can be explained by 8 items in the biodata measure (for a list of the items, see Table 7). On the Financial Planning Scenario test, 33% of the variance can be explained by 5 items in the biodata measure (see Table 8), and 43% of the variance on the Financial Planning Composite Pretest can be explained by 6 items in the biodata measure (see Table 9).

Tests of Mediation

In testing for mediation, mediators are used to establish *how* or *why* one variable predicts or causes individual levels on an outcome variable. Essentially, the mediator is a variable that explains the relationship between a predictor and an outcome (Frazier et al., 2004). If supported, a test of mediation can show that the mediator fully or partially mediates the relationship between X and Y. In a fully mediated model, the relationship between X and Y becomes null when controlling for the mediator (M). In a partially mediated model, the path from X to Y is not affected (perhaps slightly reduced) when controlling for M. It was hypothesized that biodata would partially mediate the relationship between the ability and non-ability traits and domain knowledge, since the ability and non-ability traits were expected to make a significant contribution to the prediction of domain knowledge, even when controlling for biodata.

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To test this hypothesis, Baron and Kenny's (1986) approach was used to test for mediation in addition to the path analysis. According to this approach, mediation is supported if 4 steps or criteria are met. In the first step, the distal construct (i.e., ability or non-ability traits) must relate to the outcome (i.e., domain knowledge). Second, the distal construct must relate to the mediator (i.e., biodata). Third, the mediator must relate to the outcome after controlling for the distal predictor. In the fourth step, the relationship between the distal predictor and the outcome should no longer be significant in the presence of the mediator if full mediation is to be claimed. However, if this relationship remains significant in the presence of the mediator, then partial mediation can be claimed.

In these analyses, 14 non-ability traits, Gf, and Gc were entered into separate mediation equations as predictors of domain knowledge. In addition, each of the biodata scales was entered individually as the mediator, and used to predict 1 of 3 criterion measures (i.e., Financial Planning Multiple Choice, Financial Planning Scenario test, and the Financial Planning Composite Pretest). In total, 144 tests of mediation were performed. Based on these analyses, it was found that biodata partially mediated the relationship between various non-ability/ ability traits and domain knowledge. Thus, Hypothesis 1 was partially supported. Specifically it was found that the relationship between need for Achievement and the Financial Planning Scenario test was partially mediated by the General Investment biodata scale. In addition, the relationship between Gf and all criterion measures of domain knowledge (i.e., Financial Planning Multiple Choice test, Financial Planning Scenario test, and the Financial Planning Composite

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Pretest) was partially mediated by the General Investment and Financial-related Life Events biodata scales.

Although not hypothesized, some relationships (between non-ability/ability traits, biodata, and domain knowledge) appeared to be fully mediated according to Baron and Kenny's (1986) approach. The structural equation modeling (SEM) approach to testing for mediation (James, Mulaik, and Brett, under review) was used to re-test those models that appeared to be fully mediated. The SEM approach suggests that a model is supported if b_{mx} (the b-weight from the regression of the mediator on the predictor variable) and b_{ym} (the b-weight from the regression of the criterion variable on the mediator) are both significant. In addition, it is necessary to calculate the significance of the $b_{yx.m}$ term (that is, the b-weight of the regression of the criterion variable on the predictor variable, with the mediator held constant). If this term is significant, then it can be concluded that the model is fully mediated. That is, the predictor variable only influences the criterion through its effects on the mediator (L. James, personal communication, May 25, 2005). The results from these two approaches converged, such that models deemed fully mediated by the Baron and Kenny approach were confirmed to be fully mediated models by the SEM approach. Specifically, it was found that the General Investment biodata scale fully mediated the relationship between Neuroticism and both the Financial Planning Scenario test and the Financial Planning Composite Pretest. The Sobel (1982) test was conducted to determine the indirect effect of Neuroticism on domain knowledge, and to provide convergence. According to the Sobel (1982) test, the indirect effects were 2.28 and 2.49 ($p < .05$) for the scenario test and the composite pretest respectively. In addition, the Fiscal Responsibility biodata scale fully mediated the relationship between

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Neuroticism and both the Financial Planning Scenario test and the Financial Planning Composite Pretest. The indirect effects were 2.82 and 2.93 respectively. The General Investment biodata scale fully mediated the relationship between need for Achievement and the Financial Planning Composite Pretest; however, the Sobel (1982) test for indirect effects was not significant. The Fiscal Responsibility biodata scale fully mediated the relationship between Need for achievement and both the scenario test and the composite pretest. The indirect effects were 3.35 and 3.61 respectively. The Fiscal Responsibility biodata scale fully mediated the relationship between risk-taking behavior and the composite pretest, but the indirect effect was not significant.

The General Investment biodata scale fully mediated the relationship between Other-referenced goals (MTQ; Kanfer & Heggestad, 1997) and both the Financial Planning Multiple Choice test and the Composite Pretest. Values of the indirect effects were 3.24 and 3.26 respectively. In addition, the Fiscal Responsibility biodata scale fully mediated this relationship between Other-referenced goals and the multiple choice test and the composite pretest. The indirect effects were 2.43 and 2.49 respectively.

CHAPTER 8

DISCUSSION

In general, life experiences specific to the financial domain do appear to provide predictive validity for domain knowledge within that same domain, over and above that obtained with traditional ability and non-ability measures. In addition, there is some evidence that biodata measures can be used within the realm of domain knowledge to predict performance on tests of domain knowledge, independent of ability/ non-ability traits. These preliminary findings lend support for additional research on the relationship between life experience information and domain knowledge.

In terms of using scales to classify biodata items, it may be beneficial to use scales in some cases (e.g., the General Investment and Fiscal Responsibility scales), where multiple items can be rationally combined into groups. However, in other cases (e.g., the Financial-related Life Events scale), the heterogeneity of items leads to low internal consistency reliability. Within the domain of biodata, there may be a tradeoff between looking at the predictive validity of individual items and weighting items accordingly, and developing multiple-item scales that may have more predictive power.

In addition, the current biodata measure might be improved by adding more items to each scale. Specifically, it may be beneficial to have multiple biodata items about specific life experiences (e.g., multiple items about divorce, retirement savings accounts, etc) so that it is possible to create smaller, more cohesive clusters of experiences to be used as scales for the measure. This might allow for a more detailed understanding of the relationship between financial-related life experiences and domain knowledge than what is understood through the broader scales used in the current study.

Since context of experience was measured with a single item in the current study, it cannot be clearly concluded from the results whether the context of experience influences domain knowledge. In future investigations, it may be beneficial to use a more extensive measure to evaluate each potential context of experience. A more powerful analysis of experience context may enable the researcher to draw more substantial conclusions as to whether the context of experience exerts some influence on domain knowledge.

It is interesting that the Financial-related Life Events biodata scale is significantly negatively correlated with Gf, and is not significantly correlated with domain knowledge on the financial issues tests. This finding may be due to the fact that many of the items in the Life Events scale focus on negative life events, such as incurring debt, experiencing divorce, and collecting unemployment. In developing the biodata measure, the majority of these items were not reverse scored because it was believed that even some negative life events might lead an individual to be more knowledgeable about various financial issues. In future studies, it may be necessary to differentiate between negative life events that may lead to increased financial knowledge (as a result of seeking help on how to handle certain situations successfully and learning from one's mistakes), and negative life events (perhaps, *recurring* negative life events) that are indicators of personal negligence or lack of interest. Additionally, because the items within the Life events scale cover a variety of topics within the financial domain (e.g., divorce, unemployment, etc), the correlations may have been affected by the multidimensional nature of the scale. As discussed previously, it would be beneficial to include multiple items about each life

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event so that smaller, more detailed scales could be used in the prediction of domain knowledge.

The use of trait complexes in the path models allows for more interesting interpretation of the model than does the use of non-ability traits. When the trait complexes were entered into a path model, the math/science/financial trait complex and the achievement-oriented trait complex were positively related to the biodata measure, while the social/enterprising trait complex was negatively related to the biodata measure. When Gf and Gc were entered into a path model along with the trait complexes, the math/science/financial and achievement-oriented trait complexes were most predictive of biodata. In this model, Gf was negatively related, and Gc was positively related to the biodata measure. The relationship between Gc and biodata was expected given that Gc is a measure of intelligence gained through occupational and avocational experiences. Based on research which suggests that ability will set the upper bound on domain knowledge (e.g., Ackerman, 1996), the negative relationship between Gf and biodata is somewhat surprising. Although it is logical that Gf would set the limit on success within a given domain, it is unknown whether Gf influences the desire to self-select to certain experiences. This may account for the negative relationship between Gf and biodata.

Ultimately there does appear to be some benefit to using life experiences within a given domain to predict knowledge within the same (or related) domains. On a larger scale, it would be useful to determine whether this same method could be applied to additional domains. Specifically, whether additional biodata measures could be rationally developed and used to predict domain knowledge in various domains.

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In revising the current measure, attention should be placed on evaluating the items that were identified by the stepwise regression as being the most predictive of financial issues knowledge. In future investigations, it will be important to understand the fundamental nature of biodata. That is, what is it about these biodata items that enable them to predict knowledge? It has been suggested that biodata items are so predictive because they capture a wide range of information, beyond what is captured with traditional personality measures (e.g., Mumford & Owens, 1982). Unfortunately, it is still unknown what this “wide-range” of information includes. Additional research could focus on identifying the elements of life experiences that are useful in predicting knowledge.

The use of the stepwise regression procedure was helpful because it identified the specific items that were most predictive of domain knowledge. Although it is not abundantly clear whether there is an underlying relationship between the items, there are a few potential explanations for the predictive validity of these specific items. For example, the biodata items that were most predictive of the financial planning scenario test (Table 8) were closely related to issues that were presented on the scenario test. People who reported a given experience on the biodata measure should be expected to be more successful on a scenario test item of the same or similar content. A similar result was found for biodata items that were most predictive for the financial planning multiple choice test. Specifically, the most predictive biodata items were similar in content to items on the multiple choice test. This finding is consistent with Asher’s (1972) suggestion that accurate prediction is obtained with a point-to-point correspondence between items in the predictor space and the criterion.

Additionally, it may be useful to evaluate the reciprocal relationship between biodata, personality, interests, and ability. In the current study, affective, cognitive, and conative traits were placed as causally prior to the biodata measure, as the biodata measure focused on experiences that were assumed to take place later in life, presumably after the individual's personality and interests had been developed. In Mael's (1991) discussion of the Social Identity Theory, he proposed using this theory in connection with the Ecology Model for a more comprehensive model. This new model would include those life experiences that are causally prior to the development of personality, interests, and ability, and are typically outside of the individual's control, and those life experiences that are choice-based adaptive responses made by the individual. Thus it may be useful to develop domain-specific biodata measures that tap those elements of experience that the individual could not control, and those experiences that were choices made by the individual. Both types of experience may have important implications for the use of biodata in the prediction of domain knowledge.

Support for the use of biodata in performance research is based on the argument that life experience information can add unique value to the prediction of performance. Specifically, that overlap among sets of predictor variables is minimal. The General Investment and Financial-related Life Events biodata scales were significantly correlated with Gf, ($r=.23$ and $-.25$, $p<.01$, respectively). In contrast, the biodata scales were not significantly correlated with Gc. Significant correlations between the biodata scales and the personality traits ranged from $r= -.19$ to $.35$. Significant correlations between the biodata scales and motivational traits ranged from $r=-.21$ to $.34$. While these significant

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correlations indicate that there is some overlap between predictors, the biodata measure does appear to provide incremental predictive validity for domain knowledge.

Conclusion and Future Implications

The purpose of the current study was to apply the use of life experience information to the prediction of domain knowledge. Because results from the current study show that the biodata measure can be used in the prediction of domain knowledge, it may be possible to use this measure and/or develop additional domain biodata measures to serve as indices of domain knowledge for various domains. Specifically, in the absence of an established domain knowledge test for a particular domain, a domain-specific biodata measure could be administered to provide an estimate of the individual's degree of knowledge within that domain.

Limitations of the Study

The biodata measure used in this study was rationally developed, and was created to specifically target experiences within the domain of finance. As such, a potential limitation of this study is that while the findings will have broader implications for the use of biodata in the prediction of knowledge, the biodata measure itself will not be widely applicable to other domains.

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