ABILITY, PERSONALITY, INTERESTS, AND EXPERIENCE DETERMINANTS OF DOMAIN KNOWLEDGE ACQUISITION

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Ability, Personality, Interests, and Experience Determinants of Domain Knowledge Acquisition.

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SUMMARY

The goal of the current investigation was to examine knowledge acquisition within an ecologically valid context. The study was based on an investment theory of intellectual development that incorporates the roles of ability, existing knowledge, interests, and personality variables in knowledge acquisition. Prior knowledge and knowledge acquired was assessed for two knowledge domains (health/cardiovascular disease and technology/xerography) with a sample of 199 adults between the ages of 19 and 68 living in the community. The learning context included a 30 min video followed by independent study with homework materials. Results indicated that prior knowledge and ability were important predictors of knowledge acquisition for both video and homework learning. Also, the relationship between these predictors and knowledge acquisition changed as a function of knowledge domain examined and learning environment. Non-ability traits showed generally negligible relations with knowledge acquired. However, more objective non-ability measures such as biodata (i.e., life history) measures and whether or not the participant took notes during the learning modules were predictive of knowledge acquisition.

CHAPTER 1

INTRODUCTION

The human mind can be thought of as having three different aspects, cognitive, conative (i.e., motivation or will), and affective. This three-part consideration of the mind has a long and established history in psychology (Hilgard, 1980). Yet, research within one of these areas is often conducted in isolation of the other two. As pointed out by Ackerman (1997), the different aspects of the mind can be considered to be different principalities in what Cronbach (1957) called the "Holy Roman Empire" of the discipline of correlational or differential psychology. Ackerman further states that, "Though these principalities have long been neighbors these many decades, some barriers between them have been maintained or even raised over the years – to the degree that many students of one specialization have little or no contact with the other fields" (Ackerman, 1997, p. 171-172). For example, investigations of learning within the correlational discipline tend to focus on how individual differences in a single area (i.e., cognitive, affective, or conative) differentially predict learning outcomes (Snow, 1986). Although this research has been informative about the types of individual differences traits that might influence learning, such research generally provides little information about the specific processes involved in learning or how ability and non-ability traits interact to affect learning outcomes.

In experimental research, the separation of cognitive, affective, and conative components can be understood as an attempt to control extraneous variables that might influence the outcomes of the different treatments being investigated. In experiments of new learning for example, the desire for control over the influence of prior knowledge leads researchers to examine learning for abstract and nonsense information in decontextualized environments (e.g., Peterson & Peterson, 1959). Although these experiments may be informative about the processes relevant to learning within the parameters of each experiment, they may actually provide little information about the processes involved in knowledge acquisition in an ecologically valid context. That is, in the real-world, the amount of information learned by an individual may be influenced by individual differences in preferences, motivation, temperament, prior experiences, existing knowledge, and intellectual ability (Ackerman, 1996).

Some researchers have bridged the gap between experimental and correlational disciplines by examining how different aspects of the learning environment (e.g., educational treatments) might interact with traits to affect learning outcomes (Snow, 1989). This line of research on aptitude-treatment interactions (ATIs) has been informative about how the learning environment affects learning outcomes for certain types of learners. An example of an ATI frequently cited is that individuals of lower ability benefit relatively more from increased structure in a learning environment, while those of higher ability benefit relatively more from less structure (Snow, 1989). However, the focus of ATI research has been on the interaction between the environment and individual differences traits in achievement or educational settings. As such, this research does not specifically examine the roles of non-ability and ability traits in the process of domain knowledge acquisition for adults.

The investigation presented here was an attempt to go beyond current research on learning by examining knowledge acquisition within a context that was more ecologically valid than the controlled settings of most experimental studies. By removing much of the experimental control exercised in typical learning experiments and by examining knowledge domains that have real-world relevance, it was hoped that the roles of prior knowledge and experience, motivation, and personality in knowledge acquisition could be more fully examined. A research program pursued by Ackerman and colleagues suggests that individual differences in cognitive ability and non-ability traits are potentially important predictors of existing knowledge (Ackerman, 2000; Ackerman, Bowen, Beier, & Kanfer, 2001; Ackerman & Rolfhus, 1999; Beier & Ackerman, 2001; Beier & Ackerman, 2003; Rolfhus & Ackerman, 1999). The current investigation expanded this research by including both ability and non-ability traits as predictors of knowledge *acquisition*. The use of a broad range of predictors was informative about the individual differences traits, and their interactions, that potentially lead to the acquisition of domain knowledge. The findings are potentially important for identifying the ability and non-ability factors that may predict learning across contexts (e.g., in educational and vocational settings).

CHAPTER 2

LITERATURE REVIEW

The current study was framed within a theory of intelligence that addresses the roles of ability and non-ability traits in intellectual development through the adolescent and adult lifespan. The theory and the traits proposed as important in knowledge acquisition are described below. The approach is broad -- the relevant traits include cognitive ability, existing domain knowledge, motivational traits, interests, and life history or experiences. Research on cognitive ability and adult intellect will be reviewed first, followed by a description of the theoretical basis for the study. The role of prior knowledge and potentially relevant non-ability traits such as personality, interests, and life history will then be discussed.

Cognitive ability

Although there are many different definitions of cognitive ability (e.g., see Sternberg, 1990), there is general agreement that cognitive ability is related to learning and knowledge acquisition (Snow, 1986). Some theoretical perspectives of intelligence equate performance on abstract spatial reasoning tasks with intelligence (e.g., performance on the Raven's Progressive Matrices, Penrose & Raven, 1936; or performance on working memory measures; Kyllonen & Cristal, 1990). However, many researchers propose a broader conceptualization of intelligence (e.g., Guilford, 1956; Horn & Cattell, 1966; Wechsler, 1950). This broad approach was supported by an extensive review of the literature on cognitive ability conducted by Carroll (1993). Carroll proposed a three-stratum hierarchical model of cognitive ability. At the first level, the model included a broad range of abilities that are measured (e.g., language comprehension, inductive reasoning skill). The second level contained content factors determined by the common variance among the manifest abilities at the first level. These factors included fluid intelligence (Gf; defined by Cattell, 1987, and Horn & Cattell, 1966, as the processing and reasoning component of intelligence) and crystallized intelligence (Gc; defined as the knowledge acquired through education and experience). A higher order general ability factor, or *g* was on the third level of the hierarchy. The placement of *g* at the top of the hierarchy implied that *g* is involved in performance on all cognitive tests (Snow, 1986). Evidence suggests that the general ability factor shares the most variance with Gf or reasoning ability (Gustafsson, 1984). However, in the hierarchical conceptualization of intelligence outlined by Carroll, *g* is a broad and multi-dimensional concept that is determined not only by reasoning ability but by more crystallized abilities as well.

Working memory has recently emerged as a construct related to *g* (see Baddeley, 1986 and Kyllonen & Christal, 1991). According to researchers in this area, the working memory system is concerned with the simultaneous processing and maintenance of information (Engle, Tuholski, Laughlin, & Conway, 1999). Working memory measures usually pair simple learning or reasoning tasks with simple memory tasks. These measures are relatively narrow measures of cognitive ability in that they are related mainly to Gf and processing speed. This is probably because participants can perform well on these measures with relatively minimal cultural knowledge or Gc. That is, an understanding of the alphanumeric system and the ability to recognize simple equations and sentences as correct is the only type of knowledge generally required for adequate performance on working memory tasks. Nonetheless, working memory researchers have suggested that working memory capacity and *g* are largely the same (Kyllonen & Cristal, 1990). Although this view allows a more parsimonious conceptualization of *g* than the hierarchical model discussed above, working memory measures may not be sufficiently broad to provide a complete assessment of *g*. Furthermore, recent research suggests that working memory is related to, but is not the same thing as *g*. Ackerman, Beier, and Boyle (2002) examined measures of working memory, Gf, Gc, and processing speed. Results showed that although working memory was related to *g*, the relationship was not unity (the path from *g* to working memory was .70 in a structural equation model constructed in LISREL; Jöreskog & Sörbom, 1993). Working memory measures also shared substantial variance with speeded processing in this study (the path from *g* to Perceptual Speed was .55) although speed had only a moderate relationship with *g* (path from *g* to Perceptual Speed was .34).

For adults, increased age has been associated with a decline of some intellectual abilities associated with Gf, including memory and processing speed (Cattell, 1943; Hebb, 1942; Horn & Cattell, 1966; Salthouse, 1996). Cross-sectional studies indicate that these abilities begin to decline on average, around age 20 and continue a descent throughout the lifespan (Jones & Conrad, 1933; Miles & Miles, 1932). Longitudinal studies provide a more optimistic view in that the downward slope of the decline is delayed and less steep than that found in cross-sectional studies (Hultsch, Hertzog, Dixon, & Small, 1998; Schaie, 1996). However, an eventual decline in these fluid-type abilities with increasing age is apparent in both cross-sectional and longitudinal analyses.

If a narrow conceptualization of intelligence is accepted (i.e., one that considers working memory measures or measures of reasoning ability as capturing the breadth of the construct of intelligence), the research cited above implies that adult aging has negative consequences for intellectual development. However, much of the same research that has identified the decline in Gf starting at about age 20, also suggests that the knowledge acquired through educational, vocational, or avocational experiences (Gc) remains relatively stable or may even increase through the years (i.e., at least until age 70; Jones & Conrad, 1933; Miles & Miles, 1932). Longitudinal research has also demonstrated that Gc is relatively resilient throughout the lifespan (Schaie, 1996).

For adults, measures of intelligence are used mainly to predict success in achievement settings like education or work environments. If these measures focus on a narrow conceptualization of intelligence (i.e., assessing only reasoning ability), they will likely miss a large portion of what makes individuals successful at work or school (i.e., knowledge acquired). The next section of the paper will discuss the importance of considering knowledge acquired through education and experience, or Gc, in theories of adult intellect.

The role of Gc

There is evidence that individual differences in Gc can predict success in adult endeavors. Research suggests that existing domain knowledge may facilitate the process of knowledge acquisition (Ceci & Liker, 1986; Chiesi, Spilich, & Voss, 1979; Hambrick & Engle, 2001). Gc may also influence cognitive performance in daily activities for which an individual has experience (Chase & Simon, 1973; Chi, Glaser, & Rees, 1982; Morrow, Leirer, Altieri, & Fitzsimmons, 1994). For example, in a study of racetrack patrons, Ceci and Liker (1986) found that intelligence (as measured by the Wechsler Adult Intelligence Scale) was uncorrelated with expert performance on a complex probabilistic problem solving task (handicapping at a racetrack). These researchers also found that individuals who were skilled at the complex problem-solving task spent hours at the track virtually everyday developing their expertise.

Research in the area of expertise suggests that development of expert performance is a result of deliberate practice over an extended period of time (i.e., at least 10 years; Ericsson, Krampe, & Tesch-Römer, 1994). Deliberate practice develops what Ericsson and colleagues call Long-term Working Memory (LT-WM; Ericsson & Kintsch, 1995). LT-WM is described as a readily accessible store populated with information that is more durable and stable than information in short-term working memory. According to Ericsson and colleagues, LT-WM provides experts with ready access to domain knowledge acquired in their area of expertise.

There is also evidence that expertise facilitates performance within a domain. For example, in a study of expert, mid-level, and novice chess players, Chase and Simon (1971) found no advantage for experts over novices for memory of randomly placed chess pieces on a chessboard. However, an advantage for experts was found when the pieces were placed in a strategic fashion. Chase and Simon concluded that experts were able to include more information in the "chunks" they encoded into short-term storage when pieces were placed in a manner that fit with their prior knowledge of chess. Researchers have also found that increased domain knowledge may not only improve memory within a domain, but it may change the way individuals approach problems. In a study of physics experts and novices, Chi et al. (1982) found that experts were able to organize their knowledge about fundamental principles of physics in such a way that enabled them to go beyond the information presented in physics problems to solve them.

Research in the applied domain also highlights the importance of knowledge for predicting job performance. Although cognitive ability has been identified as an important determinant of job performance across many different types of jobs (Hunter & Hunter, 1984), research also suggests that experience and knowledge play a role in job performance (usually operationalized as supervisor ratings). Hunter (1983, 1986) created and tested a model for predicting job performance that included cognitive ability, job knowledge, and work sample performance. Hunter found that the effect of cognitive ability on job performance was almost completely mediated by job knowledge. Schmidt, Hunter and Outerbridge (1986) replicated Hunter's work and included a measure of job experience (operationalized job tenure). In a structural equation model, Schmidt et al. found that job experience had a significant and substantial relationship to job knowledge. Furthermore, when job experience was not considered in the model, cognitive ability had a greater relationship with job knowledge. These findings suggest that the relationship between cognitive ability and job knowledge (and ultimately job performance) is attenuated by job experience. Additional evidence of the importance of knowledge for job performance was provided by a meta-analysis conducted by Schmidt and Hunter (1998) who found that job knowledge accounted for more variance in job performance than did measures of cognitive ability.

In the context of the lifespan trajectories of Gf and Gc discussed earlier, these findings have implications for understanding how age and job performance are related (see Salthouse & Maurer, 1996 for a review of this topic). Because of the relative stability of Gc over the lifespan, it is perhaps not surprising that meta-analytic research has found either no relationship between job performance and age (McEvoy & Cascio, 1989), or a positive relationship between job performance and age (using productivity as the criterion for job performance; Waldman & Avolio, 1986). Morrow et al. (1994) also found that experience reduced age differences in performance on complex tasks relevant to the domain of air traffic communication.

The research cited above suggests that in the domain of adult intellectual performance (i.e., in jobs or avocations), a narrow conceptualization of intelligence will miss a large component of what makes adults successful in achievement settings – their knowledge and experience. The research discussed in this section also highlights why this might be true – prior knowledge provides a structure in which new information is more easily integrated. In this way prior knowledge is a potentially important determinant of the acquisition of new knowledge.

Typical versus maximal performance

The importance of including knowledge in assessment of adult intellect can also be examined in the context of typical versus maximal performance (i.e., see Ackerman, 1994; Cronbach, 1990). That is, tests of cognitive ability solicit maximal performance from examinees told to "try their best." The outcome of this type of test performance may or may not generalize to what an individual might do in a typical performance situation. Although these measures are generally good at predicting success when a task or situation is new, such as performance in the first year of graduate training (Lin & Humphreys, 1977) or job training (Ree & Earles, 1991), they are mismatched to the criterion of interest in most applied settings – that is, what an individual would do in a typical, day-to-day performance situation (Ackerman, 1994).

In contrast, assessment of non-ability traits such as personality and interests is generally conducted using measures of typical behaviors (Cronbach, 1990). These measures ask the respondent to state their preference for situations and activities based on what is most typical of them. As suggested by Fiske and Butler (1963), one could conceive of a situation where measures of maximal personality traits would be useful (e.g., "I could give a talk to a group of people if I absolutely had to" versus "I enjoy public speaking"), but generally these measures are designed to identify more general and stable preferences.

Knowledge acquired can be considered representative of typical intellectual performance in that knowledge is the cumulative result of intellectual engagement throughout the lifespan (Ackerman, 1994, 1996). In this context the finding, discussed above, that job knowledge is a better predictor of job performance than cognitive ability is not surprising (Schmidt & Hunter, 1998). That is, it would be expected that a criterion and predictor that were matched in terms of content and breadth would maximize prediction (i.e., Brunswik Symmetry, Guion, 1991; Wittman & Suβ, 1999) and that measures of typical intellectual performance (i.e., job knowledge) would be better matched to typical day-to-day performance on the job than measures of maximal cognitive ability performance.

PPIK Theory

The PPIK theory of adult intelligence (Ackerman, 1996) includes components of both typical and maximal performance in its characterization of adult intellectual development. The PPIK theory stands for Intelligence-as-*P*rocess, *P*ersonality, *I*nterests, and Intelligence-as-*K*nowledge. The PPIK theory is an investment theory of intelligence similar to Horn and Cattell's (1966) theory of Gf and Gc. Gf/Gc theory states that the investment of Gf leads to the acquisition of Gc (Cattell, 1987; Horn & Cattell, 1966). Similarly, PPIK theory posits that the investment of Intelligence-as-Process (analogous to Gf) and the application of existing knowledge structures leads to the development of Intelligence-as-Knowledge (analogous to Gc). In Ackerman's theory, the measurement of Intelligence-as-Knowledge is broader than the traditional operationalization of Gc. That is, measures of Gc have traditionally been limited to a narrow range of knowledge acquired mainly in academic settings. The measurement of Intelligence-as-Knowledge strives for breadth of assessment and potentially includes domain knowledge across a range of experiences (e.g., school, work, or leisure).

An important element of the PPIK theory (Ackerman, 1996) is the inclusion of personality and interest factors that potentially influence the direction and intensity of the effort expended to acquire knowledge. According to the theory, non-ability components such as personality, interests and motivational traits direct ability to the acquisition of knowledge. Research conducted to support the PPIK theory has identified Gf, Gc, age, and some non-ability traits as important predictors of existing knowledge in various academic and non-academic domains (Ackerman, 2000; Ackerman et al., 2001; Ackerman & Rolfhus, 1999; Beier & Ackerman, 2001; Beier & Ackerman, 2003; Rolfhus & Ackerman, 1999). In this research, Gc is consistently more highly correlated with knowledge than is Gf, with the exception of knowledge in the domains of physical science and technology. In addition, age is generally positively and significantly correlated with knowledge levels within the 18 – 69 age range. In sum, this research shows that traits other than processing ability or Gf relate to existing knowledge. Whether these traits also predict knowledge *acquisition* remains to be determined.

Studies of knowledge acquisition

Even though knowledge is a potentially important element of adult success, little is known about the traits and their interactions that might be important in knowledge acquisition. Research on training in vocational settings provides some information about the relationship between prior knowledge and knowledge acquired. For example, Martocchio (1992) and Martocchio and Judge (1997) found that prior computer experience had a direct relationship to computer knowledge acquired in training. Ree, Carretta, and Teachout (1995) investigated the role of prior job knowledge in the acquisition of knowledge in training as well. This study used a longitudinal design and a large sample of air force officers in pilot training. Prior job knowledge was measured through vocational knowledge subtests of the Air Force Officer Qualifying Test (AFOQT). Measures of knowledge acquired were tests given after training, specific to training content. Ree et al. found only a weak relationship between prior job knowledge and knowledge acquisition. Prior job knowledge had a larger relationship with work sample performance than it did with knowledge acquisition in this study.

Carretta and Doub (1998) also investigated the role of ability and prior job knowledge in the acquisition of job knowledge acquired. They used the electronics information, mechanical comprehension, and auto and shop information scales from the Armed Services Vocational Aptitude Battery (ASVAB) for their prior knowledge measures and training outcomes as a measure of knowledge acquired. They found that general ability was a better predictor of knowledge acquired than was prior job knowledge – although prior job knowledge was still significantly related to knowledge acquired for most groups studied.

In the Ree et al. (1995) and Carretta and Doub (1998) studies, the measures of prior job knowledge may have been broader than the measures of subsequent knowledge used. That is, selected scales from the AFOQT and ASVAB were used as indicators of prior knowledge and knowledge acquired was operationalized as scores on a test of specific knowledge covered in training. This potential mismatch in breadth of content of the predictor and criterion may have attenuated the relationship between prior knowledge and subsequent job knowledge found in these studies (i.e., see Guion, 1991 and Wittmann & Süβ, 1999).

The role of domain knowledge in knowledge acquisition has also been investigated in the experimental literature. These studies suggest that domain knowledge is an important predictor of knowledge acquired. For example, individuals high in domain knowledge (e.g., knowledge about baseball) were better able than those with low domain knowledge to recall information about a fictitious baseball scenario -- especially information important to the progression of the game (Chiesi et al., 1979).

Other researchers have examined whether there is a compensatory relationship between domain knowledge and cognitive ability for knowledge acquisition. In an investigation of baseball knowledge, Walker (1987) found that those with more knowledge about baseball recalled more information about a novel baseball game than did those with low knowledge. In this study, those with lower ability (as measured by an Army standard aptitude test of general/technical ability) and high baseball knowledge acquired more new information about a fictional baseball game than those with high ability and low baseball knowledge. Walker suggests that this result demonstrates the compensatory relationship between domain knowledge and ability. It may be important to note though that in both high- and low-knowledge conditions, those with higher ability acquired more knowledge than those with low ability (suggesting that ability had an additive effect across high- and low-domain knowledge).

The relationship between working memory ability and knowledge acquisition has also been studied (again in the domain of baseball; Hambrick & Engle, 2002). Hambrick and Engle found that, although working memory ability had an additive effect for recall of novel baseball information, knowledge about baseball was the most important determinant of memory for a fictitious baseball game (i.e., those with high domain knowledge remembered more information about a fictitious baseball passage than did those with low domain knowledge). As Walker (1987) found with ability, Hambrick and Engle's results showed that those with high working memory capacity outperformed those with low working memory capacity across all levels of baseball knowledge. Moreover, Hambrick and Engle's results demonstrated a "rich get richer" effect in that those with high working memory received the greatest benefit from their existing baseball knowledge for acquiring new knowledge.

In these studies, ability and working memory were important predictors of knowledge acquired across all levels of prior domain knowledge. This is perhaps a function of the experimental environment limiting the application of prior knowledge for knowledge acquisition. That is, baseball expertise in these studies may have provided a framework mainly for understanding the overall structure of the baseball game and for knowing the vocabulary used. However, baseball expertise would not be relevant to many of the facts participants would be asked to remember in these studies because the players and their baseball performance statistics and histories were all fictional in the scenario presented. Examining knowledge in domains that have real-world relevance may show that prior knowledge has a larger magnitude relationship with knowledge acquisition than was found in the experiments cited here.

Personality

In the context of the PPIK theory (Ackerman, 1996), measures of personality are important in understanding the direction in which a person chooses to invest his or her attentional resources to acquire knowledge. Most personality variables have generally shown negligible relations with ability and knowledge in prior research (Ackerman & Heggestad, 1997) – even though some of these traits are significantly correlated with performance in achievement settings (e.g., the well-documented relationship between job performance and the trait of conscientiousness; Barrick & Mount, 1991).

The personality variables that have been identified as related to knowledge and cognitive ability are those associated with individual differences in intellect. For example, openness (a measure of curiosity and intellect exemplified by imagination, curiosity, and creativity; Goldberg, 1993) has been consistently positively correlated with knowledge in studies of academic and non-academic knowledge (Ackerman, 2000; Ackerman et al., 2001; Beier & Ackerman, 2001; Beier & Ackerman, 2003). Research in organizations reveals that openness is also positively related to declarative knowledge acquired in training and to training outcomes (Barrick & Mount, 1991; Colquitt, LePine, & Noe, 2000; Salgado, 1997).

Typical Intellectual Engagement (TIE; Goff & Ackerman, 1992) is another personality measure associated with individual differences in intellect. This personality inventory was designed to assess one's intellectual engagement in the context of typical performance situations (as opposed to maximal performance; Cronbach, 1990; Ackerman, 1994, 1997). In studies of existing domain knowledge, TIE was significantly correlated with openness, Gc, and measures of existing domain knowledge (Ackerman, 2000; Ackerman & Rolfhus, 1999).

In addition to those measures associated with individual differences in intellect, personality measures associated with worry, emotionality, and a conservative or traditional style are generally negatively associated with knowledge and ability (Ackerman et al., 2001). This may be because anxiety and a conservative style are related to the tendency to avoid the risks associated with participating in a new job, task, or learning experience, which may negatively influence knowledge acquisition over the lifespan (Kanfer & Heggestad, 1997).

Given the personality measures that are most related to intellect and knowledge acquisition as discussed above, a personality measure that may be directly relevant to knowledge acquisition is a measure of motivational traits developed by Kanfer and Heggestad (1997). This measure was designed to assess an individual's tendency to "approach" or "avoid" engagement in achievement settings. Motivation has been defined as the choice to initiate effort on a task, to expend a certain amount of effort, and to persist in expending effort (Campbell & Pritchard, 1976). Two broad motivational traits proposed by Kanfer and Heggestad, achievement and anxiety, refer to the general motivational disposition of the individual. These constructs can be considered as personality traits in that they are broad and stable. The achievement trait represents an approach orientation toward learning (i.e., a desire to learn) and mastery of tasks. In contrast, the anxiety trait represents an avoidance orientation typified by fear of failure and anxiety. Achievement and anxiety motivational traits refer directly to an individual's orientation to learning and performance. In the PPIK (Ackerman, 1996) framework, these non-ability traits potentially direct an individual's effort toward knowledge acquisition.

Research also suggests that proximal processes mediate the relationship between distal traits and learning and performance. Distal individual differences processes are considered to be general traits, while proximal processes are considered to be more task-specific and associated with particular situational contexts (Ackerman, Kanfer, & Goff, 1995; Chen, Gully, Whiteman, & Kilcullen, 2000; Kanfer, 1990). Examples of proximal individual differences processes include specific achievement goals, self-efficacy for a task, and self-concept in an area; examples of distal traits are cognitive ability and personality traits.

There is evidence that proximal and distal individual differences interact with task complexity (Chen, Casper, & Cortina, 2001; Kanfer & Ackerman, 1989) for performance. That is, when a task is highly complex or new, distal individual differences are more important than more proximal processes for performance. For example, in meta-analytic research, Chen et al. (2001) found that self-efficacy (i.e., a proximal process) was a better predictor of performance when a task was low in complexity and cognitive ability and conscientiousness (i.e., distal traits) were more important when the task was high in complexity. Similarly, a meta-analysis by Stajkovic and Luthans (1998) found that the relationship between self-efficacy and task performance was attenuated as task complexity increased. Research also suggests that proximal processes associated with self-regulation may actually interfere with performance when the task is complex. For example, Kanfer and Ackerman (1989) found that the introduction of goals for task performance early in the skill acquisition process (when the task was new and therefore more complex) interfered with skill acquisition in an air traffic controller task. This may have been because self-regulation associated with goal striving taxed cognitive resources that might have otherwise been devoted to learning the task. In support of this view, Kanfer and Ackerman also found that goals had a greater negative effect on performance for those lower in cognitive ability than those high in cognitive ability. In the context of knowledge acquisition, these findings suggest that distal traits (e.g., cognitive ability) will be more important predictors of knowledge acquisition when the learning activity is more complex or cognitively demanding. Proximal processes, such as goals may be more important in learning situations where the learning activity is less cognitively demanding.

It may be that maximal performance situations impose a situational press that might limit the influence of more proximal individual differences processes in a manner similar to increased task complexity. Similarly, in a more typical performance situation, proximal traits might play a more significant role in performance. Thus, in a highly constrained laboratory environment, I expect more distal individual differences associated with learning (e.g., cognitive ability) to be more highly related to learning outcomes. When the constraints of this environment are relaxed, I predict that proximal individual differences processes, like goal setting, will be more related to learning outcomes.

Interests

Like motivational processes, interests describe the direction of attention toward experiences that will lead to knowledge acquisition (Kanfer, 1990). Interests are theorized to develop through an interaction with the environment and an individual's competence in an area (Holland, 1976). That is, individuals will likely receive positive feedback when engaged in an activity at which they excel. This feedback (either by peers or simply through the satisfaction of excelling at a task) will enhance the individual's interest in the activity. When individuals receive only negative feedback because they are not competent in an activity, or their environment does not support the activity, interests and effort are likely to wane (Holland, 1976; Owens & Schoenfeldt, 1979). This interaction between life experiences and interests is hypothesized to lead individuals to develop interests in different areas, which, in turn, result in differentiated knowledge structures (Cattell, 1987; Lubinski & Benbow, 2000).

Unfortunately, most research on the development of interests is cross-sectional and therefore provides only clues about the interactions among ability, experience, interests, and the development of knowledge structures within specific knowledge domains and topics. For example, Alexander and colleagues (Alexander, Jetton, & Kulikowich, 1995; Alexander, Kulikowich, & Schulze, 1994) studied the role of interests in the development of expertise in academic domains. This research examined the interaction of knowledge and interest for prediction of text comprehension. High interest in a domain along with relatively high domain knowledge led to increased comprehension of a technical passage. If individuals were competent in an area (i.e., knowledgeable) but less interested in the passage, they were likely to understand less from the technical passage than those who were competent and interested (Alexander et al., 1995).

Ackerman and colleagues have examined the relationship between vocational interests and knowledge across various domains (Ackerman, 2000; Ackerman & Rolfhus, 1999; Beier & Ackerman, 2003). Moderate correlations were found between knowledge domains and corresponding vocational interests from Holland's vocational interest themes (Holland, 1997). For example, investigative interests (preference for thinking through problems and organizing and understanding the world; Holland, 1959, p. 36) and knowledge of the sciences were substantially correlated (e.g., $r = .41, p < .01$; Ackerman, 2000), as were artistic interests (preference for dealing with problems through self expression in artistic media; Holland, 1959, p. 37) and knowledge about the humanities (e.g., $r = .39, p < .01$; Ackerman, 2000). Realistic interests (preference for dealing with concrete, well defined problems as opposed to abstract, intangible ones; Holland, 1959, p. 36) were also significantly related to knowledge of electronics and tools/shop (e.g., $r = .42, p < .01$; Ackerman & Rolfhus, 1999).

Reeve and Hakel (2000) investigated intra-individual correlations between interests and domain-specific knowledge profiles using a large sample of high school students. As did Ackerman and colleagues (Ackerman, 2000; Ackerman & Rolfhus, 1999), Reeve and Hakel found positive relations between interests and domain specific knowledge. These researchers also found that the relationship between interests and domain knowledge was higher for "older" students (i.e., freshman versus senior year in high school). This finding is consistent with the notion that interests direct intellectual investment in the acquisition of domain specific knowledge over time (Ackerman, 1996).

It is clear that the relationship between interests and knowledge over time is mediated by the individual's experiences (i.e., one must have an experience to acquire knowledge – whether the experience is educational, vocational, or avocational). The next section of this paper discusses the potential role of life history on knowledge acquisition.

Life history/biodata

Whether an event is personally experienced or read about, an individual must have avocational, vocational, and/or educational experiences to learn. Although this assertion seems straightforward, there is relatively little research on the importance of different types of experiences (outside of classroom learning) that might lead to the acquisition of domain knowledge. Some of the research that has been conducted in this area has investigated the value of different experiences (i.e., reading and watching television) for learning. Stanovich and colleagues (Stanovich & Cunningham, 1993; Stanovich, West, & Harrison, 1995) for example, examined exposure to print as a predictor of knowledge across a variety of domains. In these studies, print exposure was measured as the participant's familiarity with publication relevant information (i.e., author recognition test). Stanovich and Cunningham found that exposure to print was a much stronger correlate of an individual's level of knowledge than was television exposure. Stanovich et al. similarly found the exposure to print was significantly positively related to knowledge level. Further, controlling for print exposure eliminated the positive relations between age and vocabulary and age and declarative knowledge in this study. Although Stanovich et al. did not use typical biodata measures, these findings suggest that the stability of Gc is, at least in part, a function of experiences that facilitate the acquisition of knowledge.

Unlike the indirect measure of print exposure devised by Stanovich and colleagues (i.e., the author recognition test; Stanovich & Cunningham, 1993; Stanovich et al., 1995) biodata measures ask individuals to directly describe events that have happened in their lives (Nickels, 1994). According to Mael (1991), there are three general categories of attributes of biodata items; (a) history (biodata items ask individuals to retrospectively describe real events in their lives. This is one dimension that defines the domain of biodata and distinguishes it from other trait assessment such as personality.), (b) methodological variables (i.e., objectivity of the items, externality of the items [the extent to which the items assess observable events], firsthandedness), and (c) job or situation relevance (Nickels, 1994). Biodata measures have been used to develop a classification of persons (Owens & Schoenfeldt, 1979). Research suggests that biodata are useful for predicting occupational attainment (Snell, Stokes, Sands, & McBride, 1994) and have been found to be valid for occupational selection purposes (Stokes & Cooper, 2001). Because they provide a measure of an individual's experience within a domain, these measures are potentially important in predicting knowledge acquisition. Further, biodata measures may capture variance associated with traits and dispositions that are related to knowledge acquisition that have not yet been adequately operationalized in current psychological instruments.

CHAPTER 3

THE CURRENT INVESTIGATION

The overall goal of this study was to examine the respective contributions of cognitive ability, prior knowledge, personality traits, interests, and life experience (and the interaction of these traits) for knowledge acquisition across two domains. Based on the PPIK theory (Ackerman, 1996), non-ability constructs such as interests and personality, and prior knowledge were expected to contribute significantly to knowledge acquisition over and above Intelligence-as-Process. The knowledge domains examined in this study, health and technology, had relevance for success in daily life and were examined in a real-world learning environment that included two learning modules with varying degrees of constraint.

Examining two knowledge domains allowed an assessment of whether the relative importance of individual traits varied as a function of domain. For example, large gender differences in existing knowledge favoring men have been found for many academic domains and for the domain of technology (difference in standard deviation units, d = 1.0; Ackerman et al., 2001; d-score greater than .80 considered large effects; Cohen, 1988). Large gender differences favoring women have been found in the domain of health (d –scores ranging from .44 for Nutrition to 1.16 for Reproductive knowledge; Beier & Ackerman, 2003). These gender differences in knowledge and the psychological variables that might account for them (i.e., differences in motivational traits, interests, goals, and experience) were further investigated in this study.

In preparation for this study, a pilot study was conducted with a sample of Georgia Tech undergraduates ($N = 167$; 80 men and 87 women) ranging in age from 18-27 ($M = 21.71$). The pilot study investigated knowledge acquisition across four topic areas: vegetable gardening, toxic waste, exercise, and food safety/sanitation. The pilot study also included assessment of interest and experiences within the topic domain, a pre-test of topic knowledge, and assessment of cognitive abilities (verbal, numerical, and spatial). The procedure for the pilot was initial assessment of prior knowledge (a 20-item pre-test quiz) and personality measures through a questionnaire. After participants completed the questionnaire, they attended a laboratory session for assessment of ability measures and a presentation of two 30 min videos on two of the topics listed above (two topics were piloted with half of the participants, two topics with the other half). After each video, a post-test of knowledge acquired from the video was administered. Post-test assessment of knowledge included the same 20 items included in pre-test quiz and an additional 20 items (for a total of 40 items). All pre-test and post-test items were specifically related to material presented in the video. There was a large effect of knowledge acquisition from pre-test to post-test for each topic in the pilot study (e.g., ranging from $d = 2.15$ for knowledge of food safety to $d = 3.28$ for knowledge of toxic waste). Cognitive ability was also significantly associated with post-test knowledge across all domains. However, personality and interest measures had consistent significant relations with only pre-test knowledge of one domain (toxic waste). Similarly, self-reported experience in a domain was uncorrelated with post-test knowledge, and only significantly positively correlated with pre-test knowledge of gardening. In summary, the relations between non-ability traits and experience and knowledge acquired were disappointing in this pilot study. Because the pre-test was administered as part of a questionnaire that individuals completed at home (outside of the testing environment), these results suggested that the laboratory environment may have limited the contribution of experience, interests, and personality traits for knowledge acquisition.

The type of learning environment created in the laboratory for this pilot study was similar to real-world structured learning environments such as course lectures and job training. However, individuals are not usually tested on knowledge acquired immediately after exposure to new information. That is, individuals usually have the opportunity to further study or explore material on their own, outside of the training experience or classroom. Whether individuals actually engage the material outside of the structured learning environment is, or should be, related to their interests, experiences, motivation, and goals.

The study reported here was designed to loosen some of the constraints of the learning environment that may have limited the contribution of non-ability traits in the pilot study and in previous studies of learning. The study attempted to replicate learning in real-world environments by including both a structured learning experience (i.e., a 30 min instructional video) and a relatively unstructured learning experience (i.e., a self-directed homework experience). The domain knowledge presented and studied in these learning experiences (or modules) was for two domains relevant to adult life: health and technology.[1] Although the relative contributions of the ability and non-ability measures for learning could not be compared directly across the video and homework learning modules (because environment was not manipulated in isolation of other factors), it was anticipated that the role of cognitive ability would be diminished as the constraint of the learning environment was relaxed (i.e., from video to homework learning).

Because the video learning environment was hypothesized to be more directly related to Gf-type cognitive abilities, it could be considered to be more cognitively "complex" than the homework learning module. However, because the homework learning module is less structured, it could be considered more "complex" in the sense of job complexity as discussed by Wood (1986) – that is, the less structured the job, the more cognitively challenging it is. It is the case that more structured jobs show lower relationships with general ability than less structured jobs (Hunter & Hunter, 1984). However, it is not structure as much as it is constraint that potentially increases the cognitive complexity of the video learning module in this study. Examples of the situational constraints involved in learning from the video are not providing participants time to explore topics they were interested in, not allowing questions, and requiring participants to remember information presented directly after the video with little time to prepare or study. Thus, the video learning environment was predicted to require focused attention and more Gf-type abilities like memory for success. In this sense, the video was more a "maximal learning experience" that required individuals to "do their best" on the

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[1] Domains selected for this study were not those included in the pilot. This was due to a desire to further examine gender differences in knowledge acquisition. No gender differences in knowledge or knowledge acquisition were found for the topic areas examined in the pilot study.

terms of the testing situation. This can be contrasted with the homework learning experience, which was designed as a more typical learning experience that was relatively self-directed (i.e., on the terms of the learner).

The distinction between domain and topic knowledge made by Alexander and her colleagues (Alexander et al., 1995; Murphy & Alexander, 2002) was used in the current study. Domain knowledge represented breadth of knowledge in a subject area. Topic knowledge represented more specific knowledge within a domain. The two broad knowledge domains examined were health and technology. These domains were selected because they were considered to be generally relevant and important in everyday life. Selecting these domains also allowed the examination of gender differences uncovered in previous research. That is, on average, men know more than women in the domain of technology and women know more than men in the domain of health (Ackerman et al., 2001; Beier & Ackerman, 2003). The specific topics that were further investigated within these broad domains were cardiovascular disease (CVD) for health and duplicating technology (xerography) for technology.

Each video learning module was approximately 30 min long. These modules included a video (or portion of a video) produced for educational purposes. Videos were obtained through Internet searches of vendors of educational materials and through the local library. Videos were evaluated and selected based on several criteria, which were: (1) whether the video was engaging, (2) the real-world relevance of the video content, (3) whether the video contained enough information to allow for a test of declarative knowledge, (4) and the format and length of the video. Before the topics were selected there were 12 videos reviewed in the domain of health (topics ranging from diseases like aging, diabetes, cancer, and CVD to exercise and fitness) and only 2 videos reviewed for the domain of technology (one on fax machines and the other on duplicating technologies – fewer choices of educational videos existed in the technology domain). Videos were evaluated by me, a faculty sponsor of the research, and undergraduates working on the project. The final decision for video selection was made by the faculty sponsor and me.

A pilot study was conducted to assess learning from the video modules selected for this study and to evaluate the items developed for assessing the pre-tests and post-tests for the videos and topical knowledge. A total of 164 Georgia Tech undergraduates (91 men and 73 women) between the ages of 18 and 27 participated in this pilot study ($M = 20.48$, $SD = 1.86$). The pilot study showed large effects of learning from the video presentation (i.e., effects greater than .80; Cohen, 1988) as follows; $d = 2.71$ for the CVD video and $d = 2.85$ for the xerography video.

Hypotheses

The relationships hypothesized below (H1 through H9 and H12) are shown in Figure 1. The same model was tested for both domains (health and technology).

The PPIK theory (Ackerman, 1996) states that Intelligence-as-Process and existing knowledge structures will be directed by interests and personality to knowledge acquisition. Thus, it was anticipated that both cognitive ability and prior knowledge would be related to knowledge acquisition.

H1: Prior domain knowledge will be significantly related to post-test performance for the video and for the homework learning experiences. These effects will be large (i.e., following the convention for the size of effects for correlation coefficients in Cohen, 1988, effects from $r = .10$ to $r = .29$ are considered small; $r = .30$ to $r = .49$ are considered medium and those over r = .50 are considered large).

I also predicted that reasoning ability or Gf would be related to knowledge acquisition. Because of the relative constraint of the video learning environment, I predicted that the association between Gf and post-test performance for the video would be direct. For post-test performance for the homework, I expected that the effect of Gf would be indirect, through Gc, and prior knowledge.

H2: Gf will be directly positively related to post-test performance for the video.

H3: Gf will be indirectly positively related to post-test performance for the homework. The effect of Gf on homework post-test performance will be mediated by Gc and prior knowledge.

I expected that interests would not be directly related to knowledge acquisition for the video because of the constraint of the learning environment. I predicted that interests would be directly related to knowledge acquisition from homework because participants would be free to explore the homework material as they desired. I also expected that interests would be positively related to homework goals (i.e., one would have greater aspirations for learning for knowledge domains that were interesting to them). The effect of experience on knowledge acquisition was expected to be mediated by prior knowledge.

H4: Interests specifically related to the topic and domain will be directly positively related to performance on the post-test for the homework learning experience. Interests will also be indirectly related to post-test performance for the homework. The indirect relationship will be mediated by homework goals.

H5: Experiences related to the domain and topic area will be indirectly positively related to performance on the post-tests for both video and homework learning. The effects of experience for post-test performance will be mediated by prior knowledge.

Motivational traits were considered distal individual differences traits and goals were considered proximal processes. For tasks low in complexity, the effects of distal traits on performance were expected to be mediated through proximal processes (Chen et al., 2001). Thus, in the context of the difference in the relative constraint of the learning environment discussed above, motivational traits were expected to be directly related to learning from the video. The effect of motivational traits was expected to be mediated through learning goals for the homework environment.

H6: Anxiety and achievement oriented motivational traits will be directly related to post-test performance for video learning. Anxiety is expected to be negatively related to video post-test performance; achievement is expected to be positively related to video post-test performance.

H7: Achievement and anxiety motivational traits will be indirectly related to post-test performance for the homework learning experience. These relationships will be mediated by homework performance goals. Although these relationships are expected to be mediated by learning goals, achievement is expected to be positively related to homework post-test performance; anxiety is expected to be negatively related to homework post-test performance. To examine whether these relationships are direct (instead of indirect as hypothesized), alternative models will be tested that include direct relationships between the anxiety and achievement motivational traits and homework post-test performance.

The video post-test might be considered a test of Gc (which is positively associated with age). However, performance on the video post-test also required significant immediate (i.e., relatively short-term) memory and reasoning ability (or Gf), which is negatively associated with age. Because of these relationships, it was expected that age would be significantly negatively related to post-test performance for the video. Increasing age was also expected to be positively related to prior knowledge, experience, and interest in both domains. The effect of age on learning from the homework was anticipated to be mediated through Gc, experience, and prior knowledge.

H8: The relationship between age and post-test performance for the homework will be mediated through experience and prior knowledge. To examine whether a direct relationship exists between age and prior knowledge (in addition to the indirect relationship through experience), an alternative model will be tested with a direct relationship between age and prior knowledge for both domains.

H9: Age will be negatively related to post-test performance for the video. The correlation between age and post-test performance on the video is expected to be $r = -.25$. This prediction is based on the relationship between age and performance on other measures of Gf with a similar sample (Beier & Ackerman, 2003).

Gender differences in levels of prior knowledge, interests, and experiences were expected for the domains investigated in this study (health and technology). It was expected that these gender differences would be accounted for by interests, experience, and prior knowledge.

H10: Gender differences favoring women will be found for post-test performance (for both video learning and homework learning) in the domain of health. Based on prior research (Beier & Ackerman, 2003) a medium effect ($d = .60$) of gender is expected for health knowledge.

H11: Gender differences favoring men will be found for post-test performance in the domain of technology. Based on prior research (Beier & Ackerman, 2003) a medium effect ($d = .30$) of gender is expected for technology knowledge.

H12: Gender differences in post-test performance will be accounted for by differences in interests, experiences, and prior knowledge.

Alternative models will be tested with direct relationships between gender and post-test performance for video and homework learning for both topic areas.

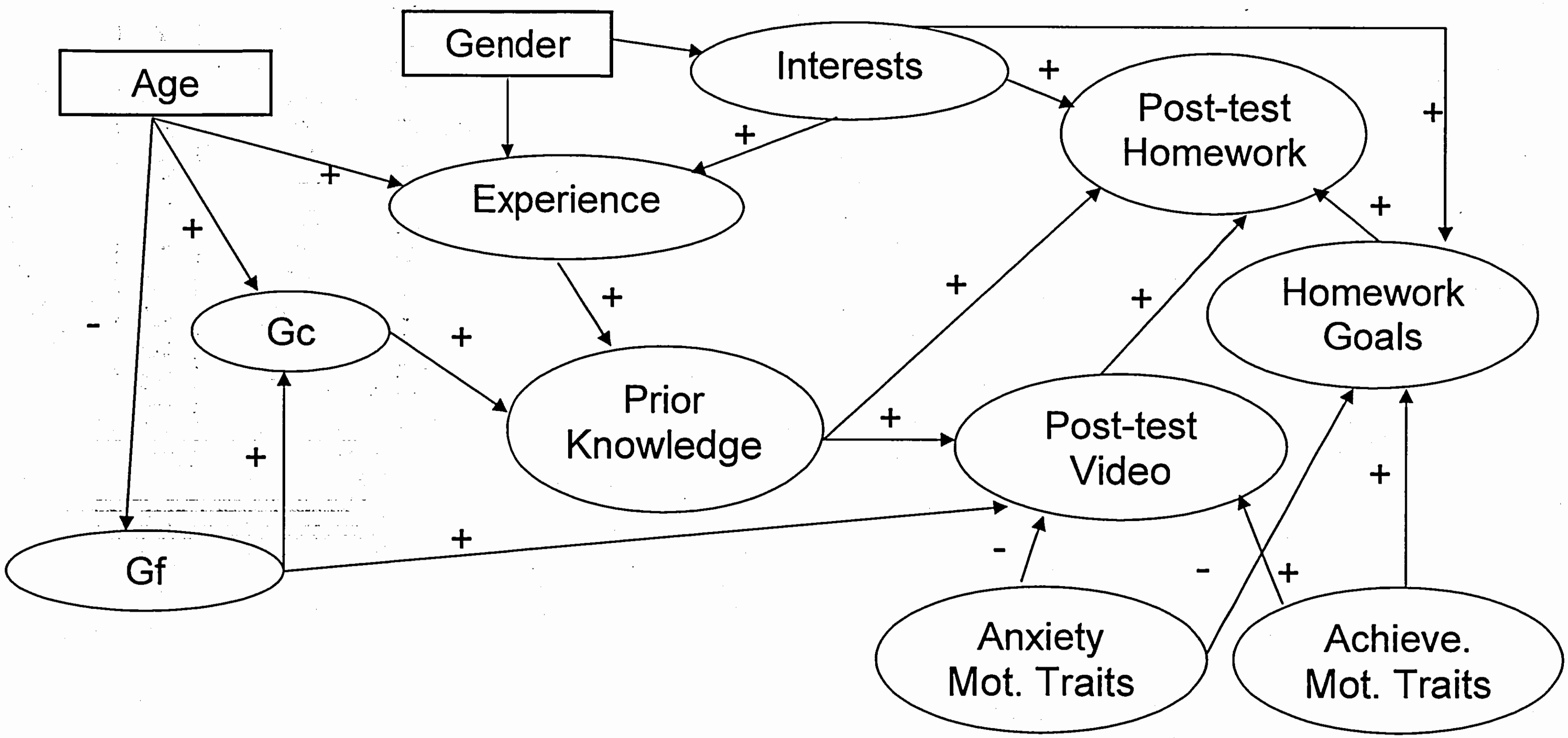

Figure 1. Hypothesized model of construct relationships across both video and homework learning modules. + represents hypothesized positive relationships, - represents hypothesized negative relationships. Gf = fluid intelligence; Gc = crystallized intelligence; Mot. = Motivational; Achieve = Achievement.

CHAPTER 4

METHOD

Participants

This study had 206 participants, recruited through the local mainstream daily newspaper, through an alternative weekly newspaper (free to the general public), or through referrals from other participants. The newspaper advertisement asked for people interested in participating in a "learning and attitude study." Seven participants were dropped from the analysis due to missing data. The remaining 199 participants (94 men and 105 women), ranged in age from 19 to 68 (M = 41.07, SD = 12.24). Requirements for participation were as follows: (1) native English speaker, (2) normal or corrected to normal vision, hearing, and motor coordination, and (3) some college education (which could include enrolling in and attending one college course). Participant demographic information is shown in Table 1.

Materials

There were four parts to this study. The first part was a questionnaire that contained the motivation, interest, demographic, and biodata measures. The second part was the ability measures, which provided assessment of Gf and Gc. The third part was the knowledge tests, which included a broad assessment of two knowledge domains and narrow tests assessing knowledge specific to topics presented in each of the learning modules. The fourth part of the study was the educational modules which took two forms: (1) a video presented in the laboratory, and (2) a homework packet that was given to participants for study on their own. Notes pages were available for participant use if

Table 1

Demographic characteristics of sample.

	Men	*Women*	*Total*	*% Total*
Sample	94 (47%)	105 (53%)	199	100
Highest level of education attained				
Some college, no degree	47	54	101	51
Associates Degree	13	16	29	14
Bachelor of Art or Science (BA/BS/BFA)	26	24	50	25
Master's of Art, Science, or Business (MA/MS/MBA)	7	10	17	09
Ph.D	1	1	2	01
Job Status				
Full-time homemakers	8	17	25	12
Full-time job	41	48	89	45
Part-time job	33	34	67	34
Job Type				
Professional/Technical/Managerial	29	38	67	34
Clerical or Sales	15	21	36	18
Service	10	9	19	9
Agricultural	0	1	1	1
Machine trades	2	0	2	1
Structural work	2	0	2	1
Miscellaneous (e.g., driver, gas attendant)	11	2	13	7
Not reported or unemployed	25	34	59	30
Other Demographic Information				
Children	38	47	85	43
Self-reported incidence of cardiovascular disease	13	25	38	19

Note. Children was scored as a dichotomous variable; 1 = has been a parent or primary caregiver for at least one child, 0 = has not been a primary caregiver for any children. Cardiovascular disease (CVD) a dichotomous variable 1 = has had in the past, or currently has CVD, 0 = does not have or has never had CVD.

desired with both video and homework learning modules.

The videos used in this study were: *Cardiovascular Disease: An introduction* (InforMed, 1993) and *The Secret Life of the Office: The Photocopier* (Team Video Pacific, 1992) A PowerPoint presentation with additional information was appended to both videos because they were under the 30 min allotted for each module. PowerPoint presentations were developed by graduate and undergraduate students using multiple resources including reference books and websites on the topic. PowerPoint presentations were reviewed by me and the faculty sponsor of the research before use.

The homework modules consisted of printed materials that provided a wider range of information than that presented in the video (from surface level information such as popular press articles to more in-depth information such as articles from scholarly journals). These materials were compiled using pre-existing educational literature and published information in the domain. This information was culled through several sources including websites (e.g., WebMD, howthingswork.com) scholarly journals (e.g., The New England Journal of Medicine), and popular press articles (e.g., Time magazine). The homework packets were assessed in terms of readability, difficulty, and how engaging the information included was (i.e., how personally involving or technical). An attempt was made to equate the two packets on these factors and to equate them on their length. Table 2 below shows the number of pages included in each homework packet and their difficulty level.

Table 2

Homework material. Number of pages by rated difficulty of text.

Topic	*Easy*	*Moderate*	*Difficult*	*Total Pages*
CVD	7	24	14	45
Xerography	8	21	15	44

Measures

Demographic information and biodata

Demographic information on participant age, gender, and level of education was collected. The biodata measures included assessment of participant experience in health, heart disease, technology, and xerography. Biodata items were developed through interviewing individuals who were considered to be generally knowledgeable about the domain. These individuals were not professionals working in the area but instead were considered experienced laypeople (there were two subject matter experts interviewed for each domain). For example, one subject matter expert in the domain of health and heart disease had a recent experience with CVD in the family; the other also had a history of CVD in the family and had a close family member working as a nurse specializing in cardiovascular care. The subject matter experts in the domain of technology and xerography expressed an interest in technical matters and proficiency at troubleshooting technical problems. Subject matter experts were asked to recount how they developed an interest in the domain (i.e., any events that had precipitated their interest), their specific experiences that might have led to increased knowledge in the area, and how their interest manifested itself in their behavior (e.g., daily diet and exercise for health and researching the latest advances in computers for technology).

In terms of Tesluk and Jacob's (1998) model of work experience, the goal of interviewing the subject matter experts in each domain was to identify those experiences that had the most "density" or developmental impact for knowledge acquisition within that domain. Tesluk and Jacobs also discussed the importance of outlining the level of specificity of life experience measures. In the context of work, their levels were task, job, work group, organization, and occupation. In terms of this analysis, the level of specification was generally on the "task" level, but included both vocational and avocational experiences. Thus, some items did ask specifically about experiences on the "job" and "work group" level as well, although mainly in the domain of technology (e.g., number of hours spent on the computer during work; whether or not others in their work group ask them to help troubleshoot problems with technology).

Biodata measures for both technology/xerography and for health/CVD were split into three sections to assess both quantitative (e.g., amount of time spent in an activity) and qualitative (e.g., how important or challenging an activity is) aspects of activities (Tesluk & Jacobs, 1998). For technology/xerography, the first part of the scale included items about the amount of time spent using technology each day. The second part of the scale asked participants to rate on a 6-point Likert-type scale (1 = Never to 6 = Everyday), the frequency with which they participate in technology related activities.

Examples of these items are, "Researching the latest upgrade to your computer" and "helped a friend or colleague with a technology problem or question." The third part of this scale asked participants to rate their level of agreement on a 6-point Likert-scale to statements about technology. Examples of these items are, "Computers do not scare me at all" and "I avoid dealing with office machines" (reversed scored).

For the health/CVD experience scale, the first part included items that pertained to the frequency with which individuals go to the doctor or hospital (either by themselves or with a family member). The second subscale included items pertaining to the frequency with which individuals participated in health related behaviors (such as working out, reading nutrition labels, and reading publications related to health and fitness). Participants were asked to rate the level of frequency on a 6-point Likert-type scale where 1 = Never to 6 = Everyday). The third subscale included items that asked participants to rate their level of agreement on a 6-point Likert with how aware they were of their own health. For example, items on this scale asked individuals to rate their level of agreement with statements such as, "I know what my usual blood pressure reading is," "I know what my overall cholesterol level is," and "I am aware of my family history of health and heart disease."

Interest

Interest measures specific to the knowledge domains and specific topics were developed for this study and asked participants to rate their level of interest on a 6-point Lykert-type scale (from 1 = "strongly dislike" to 6 = "strongly like"). Six items for each domain and topic were included (health, CVD, technology, and xerography) for a total of 24 items. Examples of the items included were "Learning a new exercise program (e.g., Pilates, Tai Chi)" for health, "Learning how to prevent heart disease" for CVD, "Researching the latest technology" for technology, and "Learning about color printers" for xerography.

Motivation and goal measures

The Motivational Trait Questionnaire (MTQ; Kanfer & Heggestad, 1997) measures three broad motivational trait clusters, achievement, anxiety, and competitiveness. The achievement trait includes appetitive or approach-oriented behavior. The anxiety trait is composed of several related constructs including general anxiety, test anxiety, and fear of failure. The competitiveness scale measures the individual's tendency to compare their performance to others and to compete in achievement situations. A shortened form of the MTQ was used in this study (48 items; Kanfer & Ackerman, 2000) with the following subscales: Desire to Learn (achievement motivation in a learning context), Mastery (goal setting with an orientation toward improvement), Worry (worry and evaluation apprehension), Emotionality (emotions associated with performance in evaluative contexts), Competitiveness (comparing performance with others with the focus on outperforming others) and Other Referenced Goals (comparing performance with others for the purpose of establishing social context).

A measure of self-set goals for learning and performance on the homework post-test was also developed for both topical areas (CVD and xerography).[2] For each topic, there were 11 Likert-type items asking individuals about their level of agreement (on a 6-point scale), as well as two additional items asking individuals how much time they intended to spend reviewing the homework material, and the score (out of 100 percent)

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[2] The implicit goal for performance for the video post-test was "do your best."

they expected to receive on the homework post-test. Examples of items used for the learning goal scale include "I look forward to learning more about this topic," and "Doing well on the quiz over this homework is important to me."

Cognitive ability and working memory measures

Twelve measures were used to identify Gf and Gc. Seven tests were administered to assess Gc: Extended Range Vocabulary, Multi-dimensional Aptitude Battery (MAB) – Comprehension, MAB-Similarities, a paper and pencil version of the Wechsler Adult Intelligence Scale-Revised (WAIS –R) Information test, the Nelson-Denny Reading Comprehension Test, Nelson-Denny reading rate, and the Word Beginnings test (a test of verbal fluency). The five measures of Gf were Problem Solving, Number Series, Spatial Analogy, Diagramming Relations, and the Verbal Test of Spatial Relations. A description of these measures is provided in Table 3.

Four measures of working memory were also included as indicators of reasoning ability (Word Sentence, Alpha Span, Computation Span, and Spatial Span; see Ackerman et al., 2002 for a detailed description of these measures). However, there were significant, unanticipated difficulties associated with administering the working memory measures in this study related to the use of a community sample (as opposed to using a Georgia Tech sample, which has been successful in the past; Ackerman et al., 2002).

The working memory measures were computerized measures administered in a group setting. The importance of prior computer experience for adequate performance on these measures was underestimated. Although not extensive, the working memory measures did require more elaborate use of the keyboard than other computerized measures used in this study (e.g., the knowledge tests). For example, some of the items asked individuals to input the first two letters of a word before it was forgotten (i.e., as quickly as they could). In this case, searching the keyboard for the appropriate letters had a negative impact performance for some participants in a way that was not related to their working memory capacity. That is, it impacted performance in a way that was not interesting in the context of the study. Administration of the measures in a group setting was also problematic in that some participants who might have had difficulty with the procedures associated with the tests may not have asked for help as readily as they would have in a one-on-one testing situation.

Table 3

Ability measures

Tests selected to represent Gc	
Extended range vocabulary test	Multiple-choice vocabulary test. Individuals were presented with a word and must choose the word that most closely matches it. The test has two parts with a time limit of 7 min each (ETS Kit; Ekstrom, French, Harman, & Dermen, 1976).
MAB-Comprehension	Test of common cultural knowledge. Items asked for the correct response to the rationale behind everyday situations. The test has one part with a time limit of 7 min (Jackson, 1985).
MAB-Similarities	Test of verbal knowledge. Each item presented two words and participants selected the option that best describes how the two words are alike. The test has one part with a time limit of 7 min (Jackson, 1985).
WAIS-R – Information	Test of general knowledge adapted from the WAIS-R Information Test for group administration. Participants attempted to complete all items. The test has one part with a time limit of 3 min (Wechsler, 1981).
Nelson Denny Reading Comp.	A test of reading comprehension with seven passages. After each passage, examinees answer several multiple choice questions. This test has one part with a time limit of 20 min (Brown, Fishco, & Hanna, 1993).
Word Beginnings	A test of verbal fluency. Participants are given three letters and asked to produce as many words that begin with these letters as possible in the allotted time. This test has two parts, each with a time limit of 3 min (ETS Kit; Ekstrom et al., 1976).

Table 3, continued

Tests selected to represent Gf

Problem Solving	Test of math word problems. The test has one part and a time limit of 5 min (created by D. Lohman; see Ackerman & Kanfer, 1993).
Number Series	Test of inductive reasoning in which a series of numbers generated by a rule is provided with the next number of the series to be identified (Primary Mental Abilities; Thurstone, 1962).
Spatial Analogy	Four-term multiple-choice test of analogical reasoning with spatial content similar in format to verbal analogy tests (i.e., A:B::C: a, b, c, d). The test has one part, with a time limit of 9 min (created by P. Nichols; see Ackerman & Kanfer, 1993).
Diagramming Relations	Test of logical reasoning. A list of three objects is presented and participants must choose a set of overlapping circles that best represents the relations among the three objects. The test has two parts, each with a time limit of 4 min (Educational Testing Services, ETS Kit; Ekstrom et al., 1976).
Verbal Test of Spatial Ability	Test of image generation and manipulation. Participants are asked to close their eyes and imagine the items described verbally. They are then asked a multiple-choice question about the items in the image. This test has one part of 24 items (Lohman; see Ackerman & Kanfer, 1993).

Note. WAIS – R = Wechsler Adult Intelligence Scale – Revised. MAB = Multi-Dimensional Aptitude Battery. Comp. = Comprehension.

The limitation of using individuals without much prior computer experience with the working memory measures was not identified before the study began. Thus, participants were not recruited based on computer experience. Due to these unforeseen difficulties, results from the working memory measures were not included in this analysis. Although this outcome is disappointing, it is perhaps beneficial that participants for this study were *not* recruited on the basis of computer experience. That is, extensive experience with computers may have restricted the range of age, ability, and experiences reported by the sample.

Prior Knowledge

Three types of prior knowledge were assessed: (1) knowledge about the broad domain (75 items each in the domains of health and technology for a total of 150 items), (2) topic knowledge specific to the video and homework material (30 items each for the video and homework modules on CVD and xerography for a total of 120 items), and (3) topic knowledge not included in the video or homework material (50 items for CVD and for xerography for a total of 100 items). The 75 items for the health knowledge test were selected from a battery of 400 items used in prior research (Beier & Ackerman, 2003). Items were selected based on their means, standard deviations, interitem correlations, and item content. Items that were specific to heart disease (12 items) in the 400 item battery were included in the heart disease topic test. Otherwise, an effort was made to include a broad range of item difficulty and item content. The 75 items used for the technology test were selected from a battery of 90 items used in prior research (Ackerman et al., 2001). Item selection for the technology domain was also based on examining the means, standard deviations and interitem correlations of the items. However, no technology items were specific to duplicating technology and therefore no items from the general domain were included in the xerography topical knowledge test.

Knowledge items specific to the learning materials were developed through analysis of the ideas presented in the knowledge modules. An effort was made to include a range of item difficulty from quite easy to difficult. An initial battery of items included (a) 30 items each related to the xerography and CVD video quizzes, (b) 51 CVD topic items, and (c) 68 xerography topic items. Based on the pilot study discussed earlier, items that demonstrated floor or ceiling effects, or did not correlate with other items in the battery were modified or excluded from further testing. A total of 30 items for the xerography topic battery was discarded or modified. Thirty-six items for the CVD topic battery were modified or replaced. Based on the pilot, seven items were modified or replaced for the video quizzes for both xerography and CVD. The final battery included 30 items each for CVD and xerography video knowledge, and 50 items each for CVD and xerography topical knowledge. The 30 homework items used in this study were created by graduate and undergraduate students and volunteers from the community who reviewed the homework packets. These items were reviewed and revised by graduate students. Homework materials, including the knowledge tests, were not included as part of the pilot study.

Notes pages

Participants had the opportunity to take notes during both video and homework modules. The purpose of recording notes was mainly as a measure of the extent to which the participant was interested and engaged in the educational module. Notes also served to make the learning experience more representative of learning experiences as they might occur in educational or industrial training (i.e., when presented with new information at work or at school, individuals generally have the opportunity to take notes if they wish). Notes were scored in three ways: (1) whether or not the participant took notes (a dichotomous variable), (2) the number of words pertinent to the topic included in the notes, and (3) quality of the notes. Note quality was scored using a list of main ideas that was developed by two independent raters for each of the four modules. For each idea written on the participant notes pages that matched a main idea, the participant was given 2 points. For each idea written that was not a main idea, but not incorrect or irrelevant, the participant was given 1 point. Words irrelevant to the topic (e.g., grocery lists, college fight songs) were not included in the total score. Percent agreement between raters on the main ideas was 85% for homework and 82% for video learning.

Self-report inventory of homework learning

The self-report of homework learning inventory included questions about the participant's activities during homework learning for both knowledge domains. Participants reported the amount of time they spent on each module and the types of study activities they participated in (10 items). Examples include "Re-read homework materials before coming to the session" and "Tried to read all of the homework material just before today's session" (reversed). (These items were identical for each domain.) Participants also reported how interested they were in the material (6 items for CVD and 4 for xerography) by rating their agreement on a 6-point Likert-scale ("1 = strongly disagree" to "6 = strongly agree") to statements such as "I am more interested in [topic] now than when I started the study" and "Overall, I thought the homework material on [topic] was interesting."[3] The topical interest measure (7 items per topic) was also re-administered in the post-homework questionnaire.

Criterion knowledge measures

Knowledge tests were administered to assess knowledge acquired in each of the four learning modules (CVD video, xerography video, CVD homework, and xerogrpahy homework). Knowledge post-tests were identical to the pre-test items for each topic (i.e., 30-items in length). The 50 topical items not directly referencing information presented in the learning modules were also given at the same time as the homework post-test for both topics (CVD and xerography).

Procedure

The general procedure for the study is shown in Figure 2. Prior to Session 1, participants were mailed the questionnaire along with an informed consent form. The questionnaire included the demographic, biodata, interest, and motivational trait measures. Participants were instructed to complete the questionnaire in a quiet, undisturbed, environment and bring the completed questionnaire and completed consent form with them to Session 1.

There were three laboratory sessions at Georgia Tech for the ability, working memory, pre-knowledge tests, videos, and criterion knowledge tests. Session 1 included approximately 45 min of ability testing for assessment of Gf/Gc and all prior knowledge assessments as follows: 75 items assessing broad domain knowledge, 50 items assessing

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[3] The difference in the number of items assessing interest in homework is related to two additional items that were added for CVD. One asked the participant to rate their level of interest in the homework material related to women, the other asked the participant to rate their level of interest in the homework material related to men.

topical knowledge not included in the video or homework, 30 items assessing topical knowledge included in the video, and 30 items assessing topical knowledge included in the homework. A total of 370 knowledge items (185 for each domain/topic area) was administered in Session 1. Knowledge items were grouped by domain (health or technology). Items referencing topical knowledge and module specific learning were intermixed (although items for CVD were separated from xerography items). The order of administration of the items was counterbalanced such that half the participants received the health/CVD related items first while the other half received the technology/xerography items first. Session 1 lasted about 3 hrs. Five minute breaks were given approximately after each hour of testing.

The ability measures were administered in paper and pencil format in a classroom setting with up to 16 participants at a time. Instructions and stop/start timings were recorded on CD and delivered over a public address system. The knowledge measures were administered in a computerized, self-paced format in individual carrels.

Session 2 was scheduled 48 hrs after Session 1. This session started with approximately 80 min administration of measures for assessment of Gf and Gc followed by presentation of both videos. Again, ability measures were administered in a paper and pencil format. The videos were shown on a 37 inch television screen in the front of the room. Instructions and stop/start timings were delivered on the video. An identical procedure was used to administer both videos as follows: Participants were given notes pages, a brief introduction to the learning module, and were shown a 30 min video. In the introduction to the video learning module, participants were informed that they would be assisting in the evaluation of educational modules to determine how much people can learn from them. They were told that during the presentation they would have the opportunity to take notes if they wished and that after the presentation they would have 5 min to study their notes before a short quiz on the information presented in the video. They were informed that their notes would not be available during the quiz. During the presentation, participants who did not wish to take notes were not made to do so. However, participants who were clearly not paying attention or sleeping were asked to focus their attention on the video. After the 30 min video, participants had 5 min to study their notes. After 5 min, notes pages were collected and a quiz was given to participants who had 10 min to complete it. Session 2 lasted approximately 3 hrs with 5 min breaks given after each hour of testing.

At the end of Session 2, participants completed a post-video questionnaire which included administration of the same interest measures included in the at-home questionnaire, the self-set learning goals for the homework for each topic area and questions about how long they intended to study the material and their expected score (out of 100%) on the post-homework quiz. After finishing the questionnaire, participants received the homework packet, which included brief instructions and notes pages. Participants were instructed (a) to study the material at their leisure before the next session, (b) that they could use additional references to find out more about the topic if they wish, (c) they should take notes if they want to, and (d) that they will be tested on the material at the beginning of the next session but their notes will not be available. Instructions were read aloud to participants and a copy of the instructions was included in the homework packet. A copy of the instructions included in the homework packet is shown in the Appendix.

To ensure ample time for participants to study the material, Session 3 was scheduled 72 hrs after Session 2. At the beginning of Session 3, homework packets and notes pages were collected and the self-report inventory of homework learning was administered. Participants were then given the computerized post-test knowledge tests for homework and topical knowledge -- a group of 160 items (30 homework learning and 50 topical knowledge items for each topic: CVD and xerography). Administration of the knowledge measures was also counterbalanced in Session 3 such that those who received the health/CVD items first in Session 1 received the technology/xerography items first in Session 3. Session 3 also included administration of the working memory measures and some additional measures that were part of a larger study not presented here. Session 3 lasted 3 hrs with 5 min breaks given after each hour of testing. At the conclusion of Session 3, participants were debriefed and compensated $120 for their participation (approximately $10 for each hour of participation).

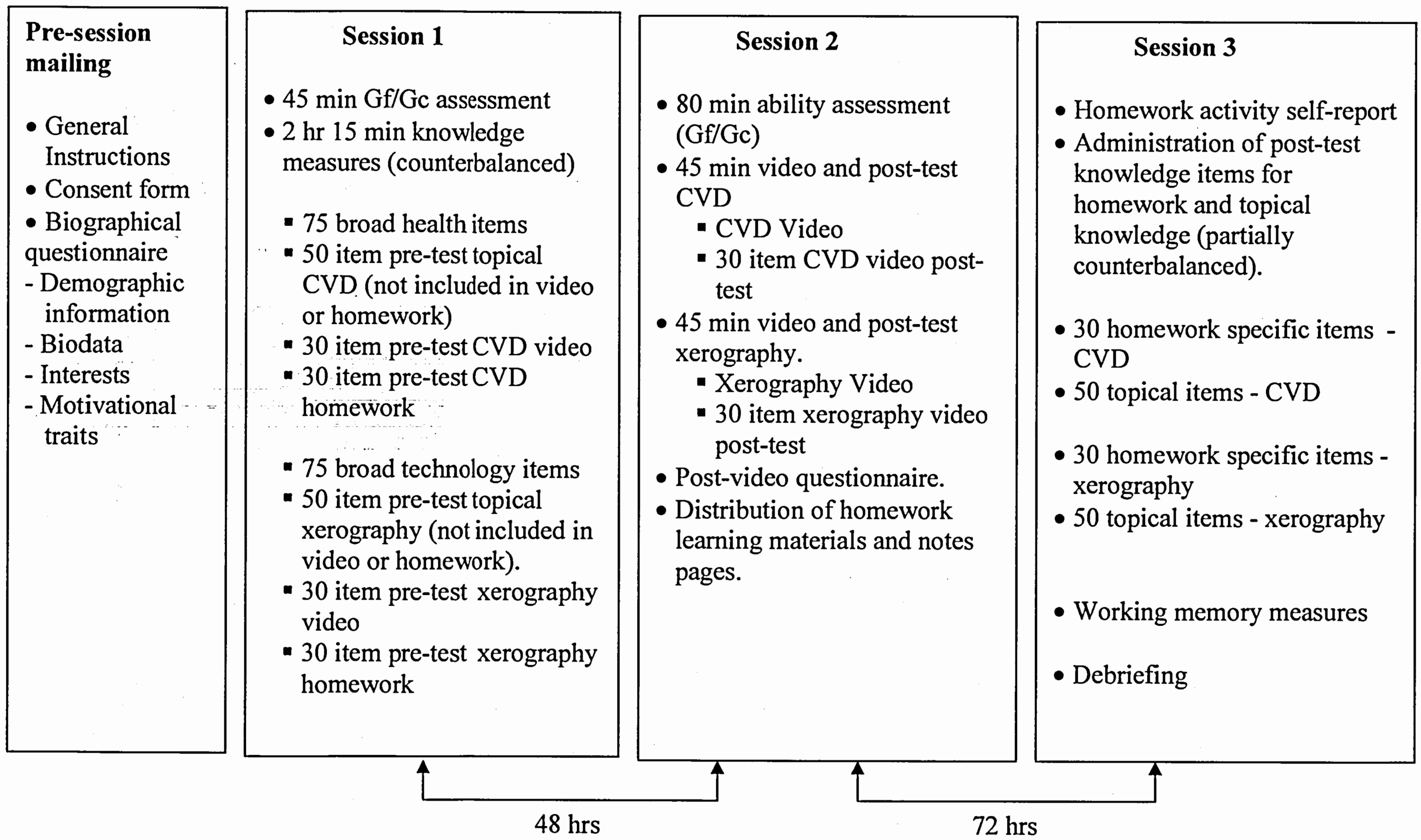

Figure 2. Graphical representation of study sessions and measures.

CHAPTER 5

RESULTS

The results section is presented in six parts. First the psychometric properties of the knowledge measures are presented along with their relations to some of the other measures included in this analysis. Next, the ability measures are presented and a rationale for creating composites for Gf and Gc is provided. Third, the interest and experiences measures are reviewed and their relations to both ability and knowledge are presented. Fourth, the motivational traits, learning goals, and study activity measures are reviewed. Fifth, measures are considered in concert through path analysis and finally, the hypotheses that had not been directly addressed through prior analyses are reviewed and tested in the sixth part.

Knowledge Measures

Descriptive statistics for the knowledge scales are shown in Table 4 along with internal consistency reliability estimates and the difference (in standard deviation units; *d*-scores) between pre-test and post test performance for topic knowledge, video knowledge and homework knowledge. Following the convention of Cohen (1988), effect sizes from $d = .20$ to .49 are considered small, those from .50 to .79 are considered medium, and those greater than .80 are considered large. An interesting pattern of effect size differences can be seen in the table and is the same for the health/CVD and technology/xerography domains. That is, effect sizes for topical knowledge acquisition are small. Medium effect sizes are found for learning from the homework across the two topic areas, and large effects are found for learning from the video.

Table 4

Knowledge Scales. Number of items, means, standard deviations, internal consistency reliabilities, effect sizes for pre- and post-tests (*d*-scores)

Knowledge Scales	*Tot. No. Items*	*Mean*	*SD*	*α*	*Pre-Post test effect size (d)*
Health Domain	75	49.82	12.53	.92	NA
CVD Topic pre-test	50	26.57	6.18	.72	
CVD Topic post-test		28.93	7.17	.82	.38
CVD Video pre-test	30	15.84	3.72	.57	
CVD Video post-test		22.35	3.86	.73	**1.56**
CVD HW pre-test	30	13.92	3.22	.44	
CVD HW post-test		16.99	4.54	.73	**.67**
Technology Domain	75	38.19	12.72	.91	NA
Xerography Topic pre-test	50	21.09	6.99	.81	
Xerography Topic post-test		23.88	7.51	.83	.35
Xerography Video pre-test	30	10.88	3.44	.55	
Xerography Video post-test		18.38	5.84	.84	**1.71**
Xerography HW pre-test	30	10.84	3.37	.49	
Xerography HW post-test		13.76	5.21	.78	**.77**

Note. N=199. Cronbach's (1951) α used as an estimate of internal consistency reliability. Effect sizes (*d*-values) for pre- and post-test learning greater than .50 shown in boldface. CVD = cardiovascular disease. HW = homework.

Individuals were not provided information directly relevant to the *topic* knowledge assessed, so the small learning effect reflects a type of carryover of learning from the other two modules. Participants were exposed to all of the content for each video, so the large effect of learning is expected because participants had no choice of information presented (although they could attend to the information to varying degrees). The medium effect size for learning from the homework was also expected because participants had some freedom to choose how much information, and which information they were going to read and attend to (i.e., they were not necessarily exposed to all the information in the homework packet). These effect sizes can be considered a manipulation check. That is, expected results were obtained in terms of the pre- and post- knowledge test differences.

With the exception of pre-tests of topical knowledge, which included 50 items (versus 30 for the other pre-tests) the internal consistency reliability estimates for the pre-tests for video and homework were low (in the .50 range). One potential reason for these low reliability estimates is that participants had no direct exposure to the information presented on the pre-tests before the learning modules. Thus, it is likely that participants guessed at the correct responses for some of the pre-test items, making responses on these pre-tests somewhat more random than responses on the post-tests (and driving down interitem correlations and internal consistency reliability). It could also be the case that the knowledge domains evaluated here are heterogeneous in the real-world. That is, most people may get bits and pieces of the knowledge at one time or another, but not in any integrated fashion.

Another notable aspect of the table is the increase in standard deviation from pre-test to post-test for five of six of the pre-test/post-test pairings. This difference was significant at the $p < .01$ level for all pre-test/post-test pairings except two: the CVD video tests and the xerography topic tests ($r = .26$ CVD topic; $r = .38$ CVD HW; $r = .56$ xerography video; $r = .48$ xerography HW; r = .05 CVD video; $r = .12$ xerography topic).[4] This increase in variability in performance after individuals were exposed to the learning module suggests that the learning experiences were difficult compared to more rote learning where one might expect less variability in performance over time (Ackerman, 1987; Zeaman & House, 1967).

The correlations among the knowledge measures are shown in Table 5. Large correlations are seen among measures in the same domain/topic area (average $r = .60$ CVD; average $r = .67$ xerography). Somewhat smaller relationships are seen for correlations between the domain/topic areas (average $r = .51$) but these correlations are still fairly substantial (between ranging from .34 to .70) suggesting one overall factor for knowledge. The table also shows that correlations between some of the pre-test/post-test measures are lower than might be expected for two administrations of exactly the same items. Specifically, the correlation between video pre-test and post-test knowledge and homework pre-test and post-test knowledge for both topic areas are in the .50 - .60 range. It may be that the low reliability of the pre-tests limits their correlations with other

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[4] A test for the comparison of two dependent variances described in Snedecor and Cochran (1967, p. 197) was used for these comparisons. The test yields a correlation coefficient which represents the correlation of the difference between the two variances and the sum of the two variances. It is based on the F-statistic as well as the correlation between the two dependent variables.

Table 5

Correlations among knowledge scales.

Knowledge Scale	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*	*10*	*11*	*12*	*13*
1. Health Domain													
2. CVD Topic pre-test	.77												
3. CVD Topic post-test	.78	.83											
4. CVD Video pre-test	.60	.62	.56										
5. CVD Video post-test	.62	.59	.65	.59									
6. CVD HW pre-test	.52	.53	.47	.43	.38								
7. CVD HW post-test	.60	.59	.64	.44	.55	.53							
8. Technology Domain	.64	.65	.70	.54	.61	.42	.56						
9. Xerography Topic pre-test	.54	.53	.57	.53	.55	.37	.56	.79					
10. Xerography Topic post-test	.58	.57	.63	.51	.58	.39	.59	.79	.81				
11. Xerography Video pre-test	.49	.50	.53	.45	.45	.36	.45	.65	.66	.63			
12. Xerography Video post-test	.58	.51	.58	.49	.67	.37	.58	.75	.76	.73	.56		
13. Xerography HW pre-test	.36	.37	.41	.37	.34	.37	.41	.57	.66	.61	.58	.51	
14. Xerography HW post-test	.55	.53	.57	.50	.44	.41	.64	.69	.69	.71	.51	.67	.58

Note. $N = 199$; CVD = cardiovascular disease; HW = homework. All correlations significant at the $p < .01$.

measures (in this case, the "other" measure is the identical scale, but after the learning experience).

Unit-weighted *z*-score composites for domain and topic knowledge were created as measures of prior knowledge for both health/CVD and technology/xerography. These composites included the domain knowledge scale (health or technology) and all of the pre-test knowledge (pre-tests for the video, topical knowledge, and homework knowledge). These composites were used in subsequent analyses to examine the relationship between prior knowledge and knowledge acquired in the study. The health/CVD composite and technology/xerography composite were correlated $r = .66$.

Correlations between the knowledge scales, gender, age, Gc, Gf, gender differences in *d*-score units, as well as *t*-tests for the difference between Gf and Gc correlations are shown in Table 6. Education was significantly positively correlated with performance for all knowledge scales from $r = .24$ for the xerography video pre-test to $r = .42$ for health domain knowledge. Correlations between age and the knowledge scales were, for the most part, not significant. Another interesting aspect of the relationship between age and knowledge shown in the table is a positive trend for the correlations between age and health/CVD knowledge and the negative trend for the correlations between age and technology/xerography knowledge (although many of the correlations were not significant).

Correlations between age and post-tests for video learning for both CVD and xerography were significantly negative ($r = -.14$ for CVD and $r = -.27$ for xerography), showing that age was negatively related to performance in the more constrained learning environment. Hypothesis 9 was that age would be significantly negatively related to

Table 6

Correlations between knowledge scales, education, gender, gender differences (*d*-scores), age, Gc, Gf (*t*-tests for difference)

Scale	*Education*	*Gender*	*Age*	*Gender Diff.(d)*	*Gc*	*Gf*	*t(rgc-rgf)*
Health Domain	.42**	.14*	.18*	-.29	.75**	.44**	9.68†
CVD Topic pre-test	.38**	-.02	.14	.05	.67**	.48**	5.37†
CVD Topic post-test	.35**	-.03	.07	.06	.70**	.56**	4.03†
CVD Video pre-test	.34**	.05	.07	-.10	.55**	.45**	2.56
CVD Video post-test	.39**	.04	-.14*	-.07	.73**	.63**	3.10†
CVD HW pre-test	.36**	.10	.17*	-.21	.45**	.32**	2.77
CVD HW post-test	.37**	.13	.08	-.26	.62**	.49**	3.15†
Technology Domain	.37**	-.26**	-.13	**.53**	.80**	.73**	2.49
Xerography Topic pre-test	.37**	-.09	-.13	.19	.70**	.67**	.68
Xerography Topic post-test	.37**	-.01	-.14*	.02	.72**	.72**	.01
Xerography Video pre-test	.24**	-.02	-.11	.05	.56**	.62**	-1.57
Xerography Video post-test	.30**	-.03	-.27**	.07	.77**	.74**	1.02
Xerography HW pre-test	.30**	-.05	-.08	.10	.51**	.55**	-1.12
Xerography HW post-test	.39**	-.03	.01	.07	.64**	.57**	1.77

Note: For correlations, * $p < .05$; ** $p < .01$. N = 199. A *t*-test for the difference between dependent correlations was conducted ($df = 196$). Bonferroni adjustment was used; family-wise $\alpha_{FW} = .05$; per-comparison $\alpha = .0037$. † indicates significance at the $\alpha_{FW} < .05$ level. Gender differences (*d*-values) larger than .50 shown in boldface. Positive *d*-values for gender indicate an advantage for men; negative *d*-values represent an advantage for women. Education coded as 0 = some college but no degree; 1 = Associate level degree; 2 = Bachelor level degree; 3 = Master's or Ph.D level degree. Gender coded as men = 1, women = 2.

post-test performance for the video across both domains, and that the correlation between age and post-test performance would be $r = -.25$. This hypothesis was supported. A test of the differences between these correlations and the hypothesized correlation of $r = -.25$ revealed that neither obtained r-value was significantly different from the hypothesized r-value at a $p < .05$ level. (The power for rejecting the null hypothesis for a sample of 199, a hypothesized r of -.25, and a two-tailed test at a p-level of .05 is .90; Cohen, 1988.)

Gf and Gc were both highly correlated with knowledge across all knowledge scales. Gc was more highly related to knowledge of health and CVD (as evidenced by the t-tests for the differences in correlations) than was Gf. This was not the case for the technology and xerography domain, however. There was no significant difference between correlations of Gf and Gc with the technology and xerography knowledge scales.

The table also shows the correlations between pre-test performance, post-test performance and ability (both Gf and Gc). An interesting aspect of the table is the increased relationship between test performance and ability from pre-test to post-test. For example, the correlation between CVD video pre-test performance and Gc is .55 and the correlation between CVD video post-test performance and Gc is .73. This difference in correlations was significant for CVD video learning and Gc, $t(196) = 4.07$, family-wise α (α_{FW}) = .05 (Bonferroni adjustment used; per-comparison $\alpha = .0047$), for xerography video learning and Gc, $t(196) = 4.89$, $\alpha_{FW} < .05$, and for CVD homework learning and Gc $t(196) = 3.13$, $\alpha_{FW} < .05$. It was significant as well for CVD video learning and Gf $t(198) = 3.57$, $\alpha_{FW} = .05$. This significant increase in the relationship between ability and knowledge provides some additional evidence for the increasing complexity of these tests. That the difference is significant mainly for video learning (although it is also significant for CVD homework learning), provides some validity for the manipulation (i.e., that learning from the video is more cognitively demanding than learning from the homework – at least for xerography).

To provide context to the above discussion, correlations between age, education, gender, Gc, and Gf are shown in Table 7. As can be seen in the table, a small positive and significant correlation is present between age and education. Surprisingly and unlike prior research, the correlation between age and Gc in this sample was negative and significant at the $p < .05$ level. Prior research with similar samples has found significant positive correlations (e.g., $r = .22, p < .01$; Beier & Ackerman, 2003) between age and Gc. The correlation of age and Gf was also significantly negative and larger than that found in other research ($r = -.42$ compared to $r = -.22$ as found by Beier & Ackerman, 2003).

Table 7

Correlations among select demographic and ability measures.

Measure	*1.*	*2.*	*3.*	*4.*	*5.*
1. Age	1.00				
2. Education	.19**	1.00			
3. Gender	-.01	-.01	1.00		
4. Gc	-.16*	.45**	.01	1.00	
5. Gf	-.42**	.28**	-.03	.76**	1.00

Note. * $p < .05$; ** $p < .01$. Gf = fluid intelligence, Gc = crystallized intelligence. Education coded as 0 = some college but no degree; 1 = Associate level degree; 2 = Bachelor level degree; 3 = Master's or Ph.D. level degree. Gender coded as 1 = men, 2 = women.

As can also be seen in the table, gender was not significantly correlated with ability, education, or age, providing evidence that the small gender differences found in domain knowledge are not a result of differences in ability by gender. Education was significantly correlated with ability and was also significantly correlated with age (which is perhaps not surprising given the time it takes to obtain an advanced degree).

Gender differences favoring women in the domain of health and for CVD, and gender differences favoring men in the domain of technology and for xerography were anticipated (Hypothesis 10 and Hypothesis 11). These hypotheses were only partially supported. A significant but small correlation between health domain knowledge and gender (favoring women) was found, but the effect was smaller than anticipated (hypothesized $d = .60$, observed $d = .29$). Gender differences favoring men were also found for technology domain knowledge and the effect was larger than anticipated (hypothesized $d = .30$, observed $d = .53$). No gender differences were found for CVD or for xerography knowledge for either pre- or post-tests.

Hypothesis 12 was that gender differences in knowledge would be accounted for by differences in interests, experience, and prior domain knowledge. A regression analysis was conducted to test this hypothesis. Because the only scales that showed significant gender differences were measures of domain knowledge (a component of the prior knowledge assessment), the regression analysis was conducted with gender, experience in the domain, interest in the domain and topic, and ability (in lieu of using prior knowledge as a predictor). The analysis was conducted with both health and technology domain knowledge as dependent variables. Ability measures were entered as Step 1. Entering ability first served to eliminate any variance in the dependent variables related to ability from further analysis. The analysis then became one of incremental variance accounted for by interest, experience, and gender after general mental ability had already been accounted for. The experience measures were entered as Step 2. Interest measures were entered in Step 3 for both the domain (i.e., health or technology) and topic (i.e., CVD or xerography). Only interest measures administered at the beginning of the study, prior to the knowledge modules, were included in this analysis. Gender was entered into the regression as a fourth and final step to test whether gender accounted for incremental predictive validity in knowledge after the other variables had been considered. The results of this analysis are shown in Table 8. As can be seen in the table, ability accounted for the majority of variance in knowledge for both domains. Experience in the domain also accounted for significant variance after ability for both domains. Interests failed to account for additional variance for either domain, but gender accounted for significant variance for both. Thus, Hypothesis 12 was not supported. That is, gender accounted for significant variance in domain knowledge for both domains after ability, experience, and interest in the domain had been considered. This finding demonstrates that, although the amount of variance accounted for by gender after the other variables had been considered is small (1.4% and 4.9% for health and technology respectively), gender differences were not fully accounted for by the psychological variables included here. This suggests that there may be additional variables that were not considered in this study that might account for gender differences in domain knowledge.

Table 8

Regression analysis for understanding gender differences in domain knowledge

Knowledge Scale		*Step 1* *Gf/Gc*	*Step 2* *Experience*	*Step 3* *Interest*	*Step 4* *Gender*
Health Domain	R^2 to add	.594**	.016**	.002	.014**
	Total R^2	.594**	.610**	.612**	.626**
Technology Domain	R^2 to add	.681**	.039**	.007	.049**
	Total R^2	.681**	.720**	.726**	.775**

Note: * $p < .05$, ** $p < .01$; Step 1 is a 2 degree of freedom (*df*) test; Step 2 is a 1 *df* test; Step 3 is a 2 *df* test; Step 4 is a 1 *df* test. Step 1 had 196 *df* in the denominator.

Ability Measures

Twelve ability tests were administered in this study to provide markers of Gf and Gc. One measure, the Nelson-Denny Reading Comprehension test included a separate reading rate assessment. Correlations among these thirteen ability measures are shown in Table 9. The correlations among ability measures are all positive and significant. The large magnitude of the correlations among verbal/knowledge measures (average $r = .61$) and spatial/numerical measures (average $r = .67$) provides evidence for the fluid and crystallized ability factors, and the positive manifold among all tests provides some evidence for a higher-order factor.

Table 9

Ability measures. Number of items, means, standard deviations, and inter-correlations.

Ability Measure	*Items*	*M*	*SD*	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*	*10*	*11*	*12*
1. PMA Number Series	20	6.35	4.61												
2. ETS Diagramming Relations	30	11.79	8.42	.68											
3. Problem Solving	15	2.61	2.70	.59	.63										
4. Spatial Analogy	30	8.42	7.99	.74	.74	.58									
5. Verbal Test of Spatial Ability	24	7.26	5.41	.67	.72	.64	.69								
6. WAIS-R Information Test	24	12.70	4.85	.54	.59	.55	.48	.52							
7. MAB-Comprehension	28	19.16	4.81	.53	.58	.41	.50	.51	.69						
8. MAB-Similarities	34	22.39	6.90	.62	.66	.52	.61	.55	.66	.72					
9. ETS Extended Range Vocabulary	48	18.69	10.60	.49	.60	.51	.51	.50	.72	.69	.74				
10. Nelson-Denny Reading Comprehension	38	23.20	10.06	.62	.68	.47	.67	.58	.65	.72	.72	.72			
11. Nelson Denny Reading Rate	NA	253.43	105.12	.33	.33	.27	.34	.28	.27	.26	.32	.41	.43		
12. ETS Word Beginnings	Open	23.39	10.23	.50	.59	.44	.51	.53	.60	.63	.58	.63	.64	.34	
13. Cloze Test	37	28.14	14.94	.60	.67	.52	.65	.61	.64	.65	.66	.68	.72	.35	.69

Note. All correlations significant at the $p < .01$ level. MAB = Mulit-dimensional Aptitude Battery. WAIS –R = Wechsler Adult Intelligence Scale – Revised. PMA = Primary Mental Abilities. ETS = Educational Testing Service. ETS Word Beginnings was a free response test and thus there is no finite number of items. Participants indicated the line on which they were reading after 1 min for the Nelson Denny reading rate test, thus it was a single item measure.

The hypothesized two-factor structure (i.e., Gf and Gc) of the ability measures was further evaluated with confirmatory factor analysis (CFA) using LISREL 8.51 (Jörskog & Sörbom, 1993). Five tests were identified as indicators for Gf (Number Series, Diagramming Relations, Problem Solving, Spatial Analogy, and the Verbal Test of Spatial Ability). Eight tests were identified as indicators for Gc (WAIS-R Information Test, MAB-Comprehension, MAB-Similarities, Vocabulary, Nelson Denny Reading Comprehension, Nelson Denny Reading Rate, Word Beginnings, and the Cloze Test).

Because the goal of the study was not to evaluate the relationship between a higher order intelligence factor and other variables included, no higher order factor was included in the model. However, the model included a correlation between the Gf and Gc factors. The fit of the model was good, χ^2 (64, N = 199) = 131.07, $p < .05$, Root Mean Square Error of Approximation (RMSEA) = .07, Comparative Fit Index (CFI) = .97.[5] Internal consistency reliability estimates, along with factor loadings are shown in Table 10. Unit-weighted *z*-score composites of the individual ability measures were

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[5] The $\chi 2$ fit statistic has been the traditional measure used to test model fit. A non-significant value, indicating no difference between the hypothesized, constrained model, and a just-identified model with perfect fit, is desired in SEM. However, the χ^2 distribution is sensitive to large sample sizes, and thus additional fit measures are usually reported. The RMSEA is a measure of how well the hypothesized model would fit a population covariance matrix (if one were available) with unknown or optimally chosen parameter values (Byrne, 1998). Use of the RMSEA is recommended because it appears to be sensitive to misspecification in the model (Hu & Bentler, 1998; MacCallum & Austin, 2000). The commonly used guidelines for interpretation of model fit are that RMSEA values between 0 and .05 represent very good fit and values greater than .10 indicate poor fit (Byrne, 1998). The CFI compares fit of the hypothesized model against some standard (i.e., a null model). The CFI was designed to address the bias to underestimate fit shown by the Normed Fit Index (NFI; Bentler & Bonett, 1980) in samples of 200 or less. CFI values of .90 or above indicate adequate fit to the data (Byrne, 1998).

Table 10

Ability Measures. Internal consistency reliabilities, and factor loadings for Gf and Gc

Scale	*α*	*Gf*	*Gc*
PMA Number Series	.83	.82	
ETS Diagramming Relations	.90	.87	
Problem Solving	.59	.72	
Spatial Analogy	.90	.85	
Verbal Test of Spatial Ability	.77	.82	
WAIS-R Information Test	.85		.79
MAB-Comprehension	.83		.82
MAB-Similarities	.89		.84
ETS Extended Range Vocabulary	.91		.84
Nelson Denny Reading Comprehension	.94		.86
Nelson Denny Reading Rate	NA		.42
Word Beginnings	NA		.76
Cloze Test	.94		.83

Note. Gf = fluid intelligence; Gc = crystallized intelligence; MAB = Multi-dimensional Aptitude Battery; WAIS-R = Wechsler Adult Intelligence Scale – Revised; ETS = Educational Testing Service; PMA = Primary Mental Abilities. Gf/Gc loadings as indicated by LISREL confirmatory factor analysis. Correlation between Gf and Gc calculated as part of LISREL solution was .83. Cronbach's (1951) coefficient alpha used to indicate internal consistency reliability.

created for each factor. The correlation of Gf and Gc, using the composite measures was .76.

The descriptive statistics and internal consistency reliabilities shown in the table are consistent with other studies using these same measures with similar, community-based samples (Beier & Ackerman, 2001; Beier & Ackerman, 2003). Of note perhaps is the relatively low internal consistency reliability for the Problem Solving test ($\alpha = .59$) which is mainly due to the heterogeneous nature of this test and is consistent with prior research (an α of .53 found in Beier & Ackerman, 2003). All other reliability estimates are in the range of $\alpha = .77$ (Verbal Test of Spatial Ability) to $\alpha = .94$ (Nelson Denny Reading Comprehension and Cloze Test).

Interest and Experience

Descriptive statistics and correlations between the interest measures are shown in Table 11. The identical interest scales for the topics (CVD and xerography) were given at different points in the study -- prior to the beginning of Session 1, again post-video; and again post-homework. The domain interest scales were given only prior to the beginning of Session 1 and again post-video. As can be seen in the table, the correlations among different administrations of the interest measures range between $r = .57$ and .88. More notable perhaps are the moderate to high correlations found between some of the health/CVD interest measures and the technology/xerography interest measures (e.g., $r_{\text{technology pre-test, health pre-test}} = .52$), suggesting that those who expressed interest in one domain were likely to express interest in the other.

Table 11

Means, standard deviations, internal consistency reliability estimates, and correlations among interest measures

Interest scale	*Mean*	*SD*	*α*	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*
1. Health pre-test	27.81	5.18	.80									
2. Health post-video	28.09	5.30	.84	.69**								
3. CVD pre-test	27.56	5.45	.84	.87**	.71**							
4. CVD post-video	28.54	5.42	.86	.62**	.88**	.74**						
5. CVD post-homework	33.39	6.14	.88	.58**	.74**	.69**	.81**					
6. Technology pre-test	23.22	6.90	.86	.52**	.26**	.43**	.20**	.19				
7. Technology post-video	22.16	6.65	.87	.32**	.33**	.29**	.27**	.21**	.73**			
8. Xerography pre-test	22.86	6.83	.86	.49**	.24**	.41**	.23**	.22**	.82**	.62**		
9. Xerography post-video	21.54	6.64	.87	.32**	.35**	.30**	.29**	.21**	.62**	.84**	.64**	
10. Xerography post-homework	25.78	7.59	.88	.25**	.14*	.22**	.09	.22**	.57**	.62**	.63**	.70**

Note. * $p < .05$, ** $p < .001$. Cronbach's (1951) α used as an estimate of internal consistency reliability.

Mean differences in the different administrations of the same interest scales were compared to understand whether interest in the domain or topic increased or decreased over the course of the study (i.e., to understand whether the learning modules influenced interest in the domain or topic). There was no significant difference in health interest pre- and post-video, $t(198) = 1.06$, ns, suggesting that the video did not influence interest in the domain. Although small, a *t*-test revealed a significant decrease in technology interest from pre- to post-test for the video, $t(198) = 2.97, p < .05$ suggesting some influence of the video on interest in the domain. Within-subjects ANOVAs were conducted to determine whether mean differences existed in interests for the topic (CVD and xerography) from pre-test, post-video, and post-homework. In both cases, results were significant, $F(2, 396) = 232.53, p < .01$ for CVD and $F(2, 396) = 52.48, p < .01$ for xerography.

Figure 3 is a graph of the means for each administration of the topical interest measures for xerography and CVD. Examination of the means shows that in both cases, interest in the topic increased after the homework learning module, but that interests were either unchanged or lower after the video learning module. One hypothesis for why this might be so is related to the relative constraint of the video learning environment compared to the homework environment. For the video module, participants did not have the freedom to pick and choose the information they were presented. For the homework module, participants were able to explore those areas that interested them at their (relative) leisure. Participants may have found the video module more aversive than the homework module (although it is impossible to be conclusive on this point because attitude toward the learning module was not assessed in this study).

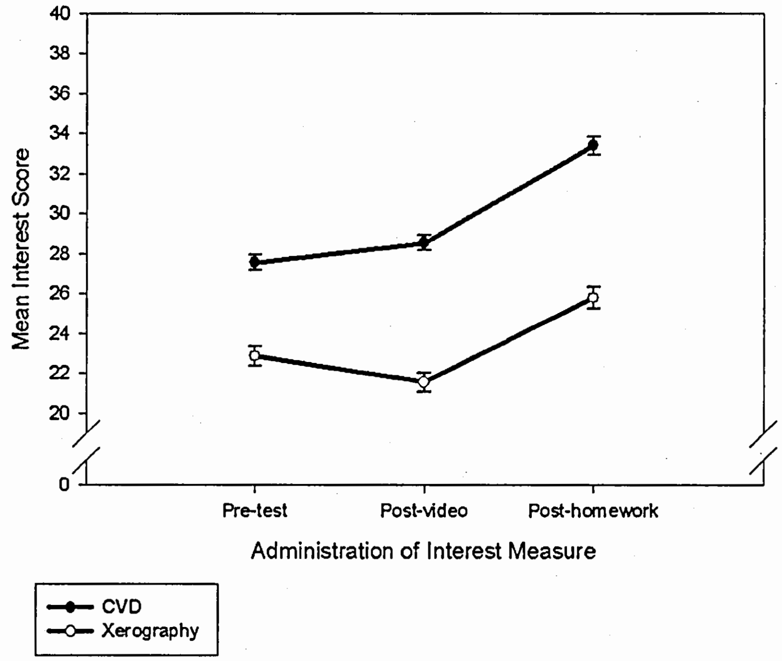

Figure 3. Means of interest measures as a function of time of administration. Pre-test measures administered prior to learning modules, post-video administered directly after the video module and post-test, and post-homework administered at the time participants handed in their homework materials, before the homework post-test. Error bars represent standard errors.

These findings imply that experience did influence topical interest in this study (negatively for the video; positively for the homework). The magnitude of the post-video/post-homework effect was medium for xerography ($d = .59$) and large for CVD ($d = .84$).

Because of the relative constraint of the video learning environment, it was expected that interests would be positively related to post-homework learning, but not post-video learning (Hypothesis 4). That is, it was thought that learning in the more constrained video environment would be predicated mainly on ability. The correlations between the interest measures, knowledge scales, and ability measures shown in Table 12 provide no support for this hypothesis. In fact, it appears that interest in health and in CVD was negatively related to knowledge acquisition for both domains/topical knowledge areas. Interest in technology and xerography was not generally related to performance on the knowledge tests, although some small positive correlations were found for technology domain interest and xerography knowledge (in the $r = .15$ range).

Also notable are the negative correlations between ability (both Gf and Gc) and interest in health and heart disease, compared to negligible relations between ability and interest in technology and xerography. This suggests that having strong interest in a domain is not necessarily enough to overcome deficits in ability for acquisition of knowledge.

There may be other, more troublesome, reasons why the interest measures failed to correlate as anticipated with knowledge acquisition. For example, it may be that individuals were likely to endorse the interest scales to present themselves in a positive light, or to please the experimenter (self-presentation and/or demand characteristics).

Table 12

Correlations between interest measures, knowledge scales, Gf, Gc, and age.

	Health Interest		*Heart Interest*			*Technology Interest*		*Xerography Interest*		
Knowledge Scale	*Pre*	*PostV*	*Pre*	*PostV*	*PostHW*	*Pre*	*PostV*	*Pre*	*PostV*	*PostHW*
Prior Knowledge Health /CVD	-.07	-.15*	-.10	-.19**	-.18**	-.05	-.03	-.03	-.09	-.05
CVD Topic post-test	-.12	-.19**	-.16*	-.22**	-.24**	.07	-.02	-.03	-.07	-.07
CVD Video post-test	-.20**	-.23**	-.22**	-.26**	-.23**	.03	-.07	-.04	-.13	-.03
CVD HW post-test	-.08	-.08	-.13	-.14*	-.15*	-.01	.00	-.11	-.08	-.06
Prior Knowledge Technology/Xerography	-.22**	-.36**	-.31**	-.44**	-.43**	.16*	.15*	.01	.01	.04
Xerography Topic post-test	-.18*	-.30**	-.27**	-.39**	-.38**	.17*	.16*	.06	.06	.08
Xerography Video post-test	-.27**	-.37**	-.35**	-.44**	-.45**	.07	.04	-.04	-.07	-.04
Xerography HW post-test	-.15*	-.28**	-.24**	-.34**	-.32**	.14*	.12	.03	.03	.12
Gf	-.23**	-.38**	-.34**	-.49**	-.51**	.08	.05	-.08	-.09	-.07
Gc	-.26**	-.38**	-.35**	-.45**	-.41**	-.01	-.08	-.15	-.17*	-.10
Age	.11	.15*	.22**	.22**	.23**	-.01	-.02	.05	.06	.10
Gender	.16*	.10	.13	.12	.09	-.14*	-.26*	-.07	-.17*	-.17*

Note. * $p < .05$, ** $p < .01$. HW = homework. Prior Knowledge Health/CVD is a composite of performance on the health knowledge scale and pre-tests for topic, video, and homework. Prior Knowledge Technology/Xerography is a composite of performance on the technology knowledge scale an pre-tests for topic, video, and homework. Gender coded as 1= men, 2 = women.

It is impossible to determine the extent to which these extraneous factors influenced the results of this study. Measures of self-presentation bias and a check for demand characteristics were not included in this study.

Even though interests were not correlated with knowledge, they were related to self-reported experience in the area, providing some evidence for convergent validity for these measures. Interest in technology and interest in xerography were correlated $r = .48$, $p < .01$ and $r = .38$, $p < .01$ with technology experiences respectively. Interests in technology and xerography were not significantly correlated with health experiences, providing some evidence for discriminant validity. Similarly, interest in health and interest CVD were significantly correlated with health experiences ($r = .44$, $p < .01$ and $r = .43$, $p < .01$ respectively), and were generally uncorrelated with technology experiences.

Correlations between the experience measures, some of the demographic measures, and the knowledge scales are shown in Table 13. As can be seen in the table, the correlations between the technology and health experience measures and the knowledge scales show some evidence of convergent and discriminant validity. For example, the correlations between technology experiences and technology and xerography knowledge are higher than the correlations between technology experiences and the health and heart disease knowledge scales (these differences are significant for two of the four correlations shown in the table). Health experiences were not related to health knowledge, but were significantly negatively related to technology knowledge. Conversely, correlations between technology experiences and technology/xerography knowledge were positive, significant, and substantial (correlations from .27 to .49).

Table 13

Correlations among experience measures, number of years in a relationship, child status, and knowledge scales, ability composites, and age.

Knowledge Scale	*Technology Experience*	*Health Experience*	*Relationship Years*	*Children*	*CVD*	*#People w/ CVD*
Prior Knowledge Health/CVD	.17*	.02	.05	-.13	.13	-.02
CVD Topic post-test	.17*	-.02	-.01	-.13	.11	-.02
CVD Video post-test	.24**	-.10	-.16*	-.20**	.02	-.06
CVD HW post-test	.18*	-.04	.06	-.16*	.02	.02
Prior Knowledge Technology/xerography	.49**	-.20**	-.10	-.18**	-.06	-.13
Xerography Topic post-test	.48**	-.18**	-.15*	-.23**	-.07	-.08
Xerography Video post-test	.37**	-.28**	-.18**	-.26**	-.12	-.12
Xerography HW post-test	.27**	-.12	-.04	-.24**	-.01	-.07
Gf	.36**	-.24**	-.25**	-.30**	-.09	-.11
Gc	.25**	-.24**	-.19**	-.28**	-.14*	-.18**
Age	-.21**	.21**	.62**	.35**	.27**	.17*
Gender	-.09	.07	.04	.04	.13	.15*
α	.90	.77	NA	NA	NA	NA
Mean	106.63	72.16	10.40	.43	.19	2.85
SD	22.21	11.74	10.25	.50	.39	3.05

Note. * $p < .05$; ** $p < .01$. CVD = cardiovascular disease. HW = homework. Prior Knowledge/health and CVD is a composite of performance on the health knowledge scale and pre-tests for topic, video, and homework. Prior Knowledge/technology and xerography is a composite of performance on the technology knowledge scale an pre-tests for topic, video, and homework. Children scored as a dichotomous variable, 1 = has been primary caregiver of at least one child; 0 = has not been primary caregiver of a child. Relationship years = number of years the participant reports being in a committed relationship such as marriage. CVD = whether the participant reported suffering from CVD. # people w/CVD is the number of people the participant reports knowing who suffer from CVD. Gf = fluid intelligence; Gc = crystallized intelligence. Gender coded as 1=men and 2 = women.

Additionally, correlations between technology experience and health/CVD knowledge were significant and positive (ranging from .17 to .24). Examination of the correlations between ability and experiences provides some context for examining the overall relationship between experiences and knowledge acquisition. That is, those participants reporting more experience in the area of technology are also higher in ability (both Gf and Gc). Technology experiences were also significantly negatively related to age. Health experiences were negatively related to both Gf and Gc, and positively related to age.

To further examine the relationship between health knowledge and health experiences, the health experiences scale was parsed into its three parts as discussed above (frequency visiting the doctor; frequency of health related activities; understanding of own health). The correlations between health knowledge and the first health experience subscale (frequency of doctor visits) were negligible and non-significant. Small negative correlations were found between health knowledge and the second health experience subscale (i.e., frequency of health related activity). Although small, positive correlations were found between the third health experience subscale and health knowledge. For example, a significant positive correlation ($r = .17, p < .05$) was found between the Health and CVD domain knowledge and this health experience subscale. Although these correlations found for this sub-scale are small, they suggest that it is the conscious awareness of health-related information (and perhaps not the frequency of doctor visits or health-related activities) that is important in acquiring health knowledge.

As can be seen in the table, the number of years in a relationship was not significantly related to most knowledge scales, but is significantly negatively related to ability measures and is positively correlated with age. Examining the data also provided some evidence that it is positively skewed -- the majority of the sample reporting very few or no years in a relationship. Whether or not the participant has children also appears to be a significant negative predictor of knowledge acquisition for some health/CVD knowledge scales and all technology/xerography knowledge scales. Although 43% of the sample has children, only 12% report being full-time homemakers (i.e., without either full-time or part-time work), so it is unlikely that lack of intellectual stimulation outside of the home is the sole cause for these negative relationships. Whether or not the individual reports having CVD is not related to knowledge of CVD or technology/xerography. This finding is in contrast with previous research that found that having direct experience with a health issue was significantly related to specific knowledge in that domain (e.g., having a child was significantly positively related to knowledge about reproduction and early life, Beier & Ackerman, 2003). The relatively low base-rate of CVD in this sample (19%) may be one reason why this relationship was not found. Not surprisingly, the occurrence of CVD in this sample and knowing individuals with CVD was positively and significantly correlated with the participant's age (age being one of the risk factors for CVD, InforMed, Inc., 1993), although the report of knowing individuals with CVD is also slightly positively skewed – that is, people reported knowing no one or relatively few people with CVD.

Note Taking

Whether or not an individual took notes for the video or homework modules was considered to be an overt indicator of participant interest in the domain and engagement in the learning activity. Note taking was scored three ways; as a dichotomous variable (whether or not the individual took notes), the number of words written down, and for quality (2-points for every main idea and 1-point for other ideas added together for a total quality score). Descriptive statistics for the notes measures are shown in Table 14. As can be seen in the table, a large portion of individuals took notes for the video (i.e., the more constrained learning environment). This number fell drastically for the homework modules for both domains. For example, for CVD, 96% of the sample took notes for the video, only 43% took notes for the homework. For xerography 91% of the sample took notes for the video and only 31% took notes for the homework.

As can also be seen in the table, the standard deviations of the homework measures for both domains are larger than the means. Skewness for the homework module distributions is over 2.0, an indicator of asymmetry in the distribution (Myers & Well, 2003). The positive skewness of these distributions is likely related to the fact that the majority of participants did not take notes for the homework for either module (i.e., 120 participants did not take notes on the CVD homework material; 140 did not take notes on the xerography homework material). To further analyze the homework notes for both domains, *t*-tests were conducted to see whether the group that took notes differed in any significant way on the interest, ability, and knowledge measure than those who did not take notes.

Table 14

Descriptive Statistics for note taking measures

Note Scoring Measure	*Mean*	*SD*
CVD Video Notes Taken	.96	.20
CVD Video, Number of Words	116.23	81.73
CVD Video Quality	22.77	13.34
CVD Homework Notes Taken	.40	.50
CVD Homework Number of Words	60.75	110.91
CVD Homework Quality	8.63	14.86
Xerography Video Notes Taken	.91	.29
Xerography Video, Number of Words	91.98	86.15
Xerography Video Quality	13.76	12.21
Xerography Homework Notes Taken	.30	.46
Xerography Homework, Number or Words	43.81	100.78
Xerography Homework Quality	5.45	12.43

Note. The "Notes Taken" measure scored as a dichotomous variable where "1" = took notes and "0" = did not take notes.

Those who took xerography homework notes differed significantly from those who did not for the xerography homework post-test, t (194) = 2.84, $p < .01$ as well as the CVD homework post-test, t (195) = 2.42, $p < .05$ (these effects sizes were medium, d = .44 for the xerography homework post-test and d = .37 for the CVD homework post-test). Those who took CVD homework notes different significantly from those who did not only for the CVD homework post-test, t (195) = 1.99, $p < .05$ (this effect size was small, d = .29).

Correlational analyses are shown below. Those who did not take notes on the homework modules were not included in the correlational analysis for the variables relevant to homework notes (as noted in the tables). This reduced the skewness of these distributions well below the 2.0 indicator of an asymmetrical distribution (Myers & Well, 2003). Correlations among the number of words and the total quality points note taking scales for video and homework across both domains are shown in Table 15. As can be seen in the table, taking more notes was highly correlated with the quality points score across all domains and modules. It also appears that those who took more notes on the CVD video, were also likely to take more notes for the xerography video as well (r = .71 between number of words for CVD video notes and xerography video notes). Taking more notes on the video modules was also related to taking more notes for the homework for CVD (r = .34) but not for xerography homework (r = .05). For those who took notes on both the homework modules (N = 48), the number of words and quality of the notes were correlated highly across the two topic areas (e.g., $r_{\text{CVD homework quality points and xerography quality points}} = .53$).

Table 15

Correlations among number of words, and total-quality score for CVD video, CVD homework, xerography video, and xerography homework notes.

Note Taking Scale	*1*	2	*3*[a]	*4*[a]	*5*	*6*	*7*[b]	*8*[b]
1. CVD Video Number of Words	1.00							
2. CVD Video Quality	.83**	1.00						
3. CVD Homework Number of Words [a]	.34**	.31**	1.00					
4. CVD Homework Quality [a]	.38**	.42**	.92**	1.00				
5. Xerography Video Number of Words	.71**	.65**	.35**	.43**	1.00			
6. Xerography Video Quality	.64**	.67**	.29**	.42**	.89**	1.00		
7. Xerography Homework Number of Words [b]	.06	.06	.44**[c]	.35**[c]	.05	.13	1.00	
8. Xerography Homework Quality [b]	.12	.17	.52**[c]	.53**[c]	.16	.30*	.91**	1.00

Note. * $p < .05$, ** $p < .01$. Columns and rows marked [a] include a reduced sample (N = 79) of those who took notes on the CVD homework. Columns and rows marked [b] include a reduced sample (N = 59) of those who took notes on the xerography homework. Cells marked with [c] include the intersection of these two reduced samples, with N = 48.

Correlations between the note-taking measures and the knowledge, interest, experience, ability, age and gender are shown in Table 16. Again, the analysis includes a reduced sample for the homework modules as noted in the table. As can be seen in the table, the number of words and quality of notes for the video module was significantly positively related to ability – both Gf and Gc. The quality of homework notes for CVD was also positively and significantly related to performance across all knowledge tests. A similar trend can be seen with the xerography homework notes, although many of these correlations failed to reach significance (perhaps a function of the reduced sample). Interestingly, note taking for the videos for both topics was also significantly and positively related to gender, indicating that females were more likely than males to take notes. Contrary to expectations, however, note taking was unrelated to interest in the domain or topic area.

Table 16

Correlations between the note-taking measures and knowledge, interest, experience, ability, age, and gender.

	CVD				*Xerography*			
	Video		*Homework*[a]		*Video*		*Homework*[b]	
Scale	*#Words*	*Quality*	*#Words*	*Quality*	*#Words*	*Quality*	*#Words*	*Quality*
Prior Knowledge Health/CVD	.19**	.25**	.23*	.35**	.35**	.39**	.13	.20
CVD Video post-test	.28**	.40**	.19	.33**	.33**	.38**	.10	.22
CVD HW post-test	.29**	.33**	.42**	.55**	.36**	.40**	.20	.37**
Prior Knowledge Technology/ Xerography	.12	.25**	.15	.29**	.19**	.26**	.10	.18
Xerography Video post-test	.15*	.32**	.13	.30**	.27**	.33**	.22	.35**
Xerography HW post-test	.15*	.23**	.12	.26*	.27**	.32**	.21	.26
Gf	.16*	.30**	.05	.22	.20**	.24**	-.01	.14
Gc	.24**	.33**	.09	.27*	.28**	.34**	.07	.19
Health/CVD Interest	.04	-.05	.05	-.05	.12	.06	-.06	-.18
Technology/Xerography Interest	-.01	.01	.02	-.05	.06	.01	-.03	-.18
Health/CVD Experience	.02	-.03	-.08	-.16	.09	.03	-.06	-.20
Technology/xerography Experience	.12	.21**	.14	.19	.12	.12	.05	.09
Age	-.13	-.23**	-.01	-.04	-.03	-.07	-.01	-.11
Gender	.32**	.25**	.13	.22*	.28**	.25**	-.16	-.01

Note. * $p < .05$, ** $p < .01$. Gender coded as 1 = men and 2 = women. Gf = fluid intelligence; Gc = crystallized intelligence. Prior knowledge a composite of domain knowledge and pre-tests for the topic, video, and homework modules for each topic. Interest measures are a composite of the domain and topical interests administered pre-test. Columns marked with [a] indicate a reduced sample of those who completed homework notes for CVD (N = 79). Columns marked with a [b] indicate a reduced sample of those who completed homework notes for xerography (N = 59).

Motivational Traits, Learning Goals and Study Activity

Descriptive statistics for the motivational trait measures and their correlations with the knowledge scales and ability composites are shown in Table 17. The motivational trait scales were largely uncorrelated with performance on the knowledge test with a few exceptions. Surprisingly, the scale that correlated most highly with test performance for topical knowledge was Worry, which correlated significantly and positively with the homework post-test for CVD, and the xerography topic and video post tests (although these correlations were small, ranging from .14 to .23). One explanation for these findings is that those who tend to be more anxious about being evaluated in achievement situations were more likely to study the homework material, or pay attention to the video material. Other-referenced goals also correlated significantly with post-test performance on xerography topic and video knowledge (these correlations were also small, $r = .18$ in both cases).

The correlations between the motivational traits and ability composites were also interesting. Correlations between Gf and Other-referenced goals, Competitiveness, and Worry scales were all modest, positive, and significant (ranging from $r = .20$ for Worry to $r = .28$ for Other-referenced goals). Correlations among the motivational traits and Gc were not significant with the exception of a small positive correlation between Other-referenced goals and Gc ($r = .19$). The relationships between the motivational traits and the ability measures found in this study are somewhat similar to those of Kanfer and Ackerman (2000), who examined the relationships among motivational trait measures and ability in a sample of community dwelling adults.

Table 17

Correlations among knowledge scales, ability measures, and Motivational Traits

Knowledge Scales	*DTL*	*Mastery*	*Other*	*Compete*	*Worry*	*Emot*
Health and CVD Domain	.02	-.08	.01	-.11	.08	.04
CVD Topic post-test	.01	-.13	.04	.03	.09	-.01
CVD Video post-test	-.09	-.07	.13	.08	.11	.04
CVD HW post-test	.03	-.08	.11	-.01	.23**	.10
Technology and Xerography Domain	-.03	-.04	.19**	.11	.14	.06
Xerography Topic post-test	-.02	-.01	.18*	.10	.19**	.06
Xerography Video post-test	-.08	-.05	.18*	.12	.14*	.04
Xerography HW post-test	-.06	-.12	.11	.06	.12	.03
Gf	-.01	.07	.28**	.24**	.20**	.09
Gc	.00	-.03	.19**	.10	.13	.02
α	.82	.78	.86	.83	.86	.80
Mean	38.80	35.41	23.86	19.39	33.41	25.91
SD	5.15	5.70	7.05	6.32	9.39	7.44
Number of items	8	8	7	6	10	9

Note. * $p < .05$, ** $p < .01$. DTL = Desire to Learn, Other = Other-referenced goals, Compete = Competitiveness, Emot = Emotionality. Gf = fluid intelligence, Gc = crystallized intelligence. HW = homework. Health and CVD Domain is a composite of performance on the health knowledge scale and pre-tests for topic, video, and homework. Technology and Xerography Domain is a composite of performance on the technology knowledge scale an pre-tests for topic, video, and homework.

That is, Kanfer and Ackerman found negligible relations between most motivational traits and ability measures as found in this study. Kanfer and Ackerman also reported a small but significant correlation of .15 between Other-referenced goals and Gf. This comparison provides some evidence that the sample and procedure used in this study were not the cause of the negligible relations found between motivational traits and knowledge acquisition.

The relationships among learning goals for the homework, and post-homework performance for both topic areas are shown in Table 18 along with other measures from the post-homework questionnaire and descriptive information. Learning goals in both topic areas showed virtually no significant relationship with pre-test or domain knowledge test performance or with homework post-test performance. One possible reason why learning goals appear to be uncorrelated with performance may also be related to extraneous variables such as self-presentation bias and demand characteristics.

The table also shows relationships between other measures given in the post-homework questionnaire and post-homework knowledge test performance. Of note, the participants' expected scores for both topic areas were significantly positively correlated with pre-test knowledge and ability, indicating that participants had a somewhat realistic view of how they might do on the post-homework test based on their prior knowledge and ability. However, expected scores were only significantly positively correlated with post-homework scores for xerography. It may be the case that for the topic of heart disease, more prior knowledge and confidence about doing well on the post-test led to less studying of the material.

Table 18

Correlations among knowledge scales, learning goals, intended time spent on homework, expected score on homework quiz, actual study activity, and homework attitude for CVD and Xerography.

	CVD						*Xerography*					
Knowledge scale	*Learning Goal*	*Intend-ed Time*	*Expected Score*	*Actual Time*	*Study Activity*	*HW Attitude*	*Learning Goal*	*Intend-ed Time*	*Expected Score*	*Actual Time*	*Study Activity*	*HW Attitude*
Prior Knowledge Health /CVD	-.04	-.08	.30**	-.23**	.02	-.11	-.12	.01	.20**	-.09	-.01	.02
CVD HW post-test	-.06	-.08	.06	-.12	-.00	-.07	-.10	-.08	.07	-.04	.02	-.03
Prior knowledge Technology/xerography	-.33**	-.19**	.17*	-.23**	-.16*	-.24**	-.04	-.16*	.30**	-.18*	-.12	.09
Xerography HW post-test	-.22**	-.11	.11	-.18**	-.01	-.21**	-.04	-.09	.18**	.01	.07	.16*
Gf	-.42**	-.23**	.23**	-.28**	-.24**	-.38**	-.19**	-.19**	.27**	-.23**	-.18**	-.10
Gc	-.28**	-.20**	.19**	-.35**	-.13	-.28**	-.19**	-.14	.20**	-.22**	-.11	-.08
α	.87	NA	NA	NA	.56	.76	.86	NA	NA	NA	.49	.79
Mean	50.97	80.4	86.39	79.88	5.16	25.44	44.05	64.61	79.59	67.67	4.51	13.13
SD	9.12	70.10	10.27	114.45	1.88	5.53	9.71	50.42	14.58	63.16	1.67	4.70
Number of items	11	1	1	1	10	6	11	1	1	1	10	4

Note. * $p < .05$, ** $p < .01$. HW = homework. Prior Knowledge – Health/CVD is a composite of performance on the health knowledge scale and pre-tests for topic, video, and homework. Prior Knowledge – Technology/xerography Domain is a composite of performance on the technology knowledge scale and pre-tests for topic, video, and homework. Gf = fluid intelligence; Gc = crystallized intelligence. Cronbach's (1951) α used as an estimate of internal consistency reliability.

The correlations among the learning goals and post homework questionnaire measures for each topic area are shown in Table 19. These correlations are, for the most part, substantial and positive indicating that participants who were likely to endorse a positive attitude about the homework, were also likely to report more significant study activity including expected time for study, and higher learning goals. Interestingly, expected score on the post-homework test does not correlate significantly with any of the other scales included in the measure for either of the topic areas (even though it was one of the only measures associated with performance on the knowledge tests). Perhaps individuals had a more objective view of how they would do on the post-test based on their prior knowledge and ability – which was apparently not influenced by their attitudes about the experience.

Table 19

Correlations among homework learning goals, intended time on homework, expected score on homework, and post-homework questionnaire measures for both topic areas.

Scale	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*	*10*	*11*
CVD											
1. Learning Goal											
2. Intended Time on HW	.21**										
3. Expected Score on HW	.19**	-.04									
4. Actual time on HW	.18*	.37**	.05								
5. Study Activity	.30**	.23**	.01	.23**							
6. HW Attitude	.62**	.22**	.08	.23**	.41**						
Xerography											
7. Learning Goal	.50**	.20**	.16*	.18*	.24**	.27**					
8. Intended Time on HW	.26**	.73**	-.01	.22**	.22**	.18*	.35**				
9. Expected Score on HW	.04	-.11	.66**	.05	-.04	-.04	.34**	.01			
10. Actual time on HW	.19**	.35**	-.01	.42**	.33**	.27**	.23**	.38**	.01		
11. Study Activity	.26**	.20**	.05	.21**	.62**	.33**	.29**	.25**	.09	.50**	
12. HW Attitude	.18*	.09	.09	.19**	.21**	.31**	.54**	.27**	.30**	.40**	.49**

Note. * $p < .05$, ** $p < .01$. CVD = cardiovascular disease. HW = homework.

Putting it Together -- Model Construction

A path model was constructed in LISREL 8.51 to test Hypotheses 1 through 8. The proposed model (identical for each domain/topic area), along with the hypothesized direction and value (positive or negative) of the paths was shown previously (in Figure 1). The variables included in the model were: (a) age, (b) gender, (c) the composite measures of Gf and Gc, (d) the prior knowledge composite measures for health/CVD and technology/xerography knowledge (a composite of domain and pre-test knowledge), (e) a composite of interest measures that included pre-test health and pre-test CVD interests and pre-test technology and pre-test xerography interests, (f) the experience measures for health and technology, (g) composites of the achievement and anxiety motivational traits, and (h) the homework learning goals measure for each topic area. Measures of video post-test performance and homework post-test performance served as criteria for the models. The correlations between the composite measures used in the model are shown in Table 20 (health/CVD) and Table 21 (technology/xerography). Power analysis revealed power of .67 to find close fit (RMSEA between .00 and .05) and power of 1.0 to find acceptable fit (RMSEA between .05 and .08) with a sample of 199, 48 degrees of freedom, and an α of .05 (MacCallum, Browne, & Sugawara, 1996). In other words, there was sufficient power to be able to rule out lack of power if the model did not fit at the RMSEA = .08 level.

Table 20

Correlations of measures included in the path analysis for health/CVD.

Measure	*1.*	*2.*	*3.*	*4.*	*5.*	*6.*	*7.*	*8.*	*9.*	*10.*	*11.*	*12.*
1. Age	1											
2. Gc	-.16*	1										
3. Gf	-.42*	.76*	1									
4. Gender	-.01	.01	-.03	1								
5. Health Experience	.21**	-.24**	-.24**	.07	1							
6. Health Prior Knowledge	.17*	.73**	.51**	.08	.02	1						
7. Health Interests	.17*	-.31**	-.29**	.15*	.45**	-.08	1					
8. CVD Post-video	-.14*	.73**	.63**	.04	-.10	.66**	-.21**	1				
9. CVD Post-HW	.08	.62**	.49**	.13	-.04	.65**	-.11	.55**	1			
10. Achievement	-.01	-.02	.03	-.03	.29**	-.04	.35	-.09	-.03	1		
11. Anxiety	-.17*	.09	.16*	.09	-.04	.07	-.15*	.09	.18**	-.24**	1	
12. CVD Learning Goals	.28**	-.28**	-.42**	.06	.34**	-.04	.51**	-.12	-.06	.23**	-.14	1

Note. * $p < .05$, ** $p < .01$. Gc = crystallized intelligence, Gf = fluid intelligence. Gender coded as 1 = men and 2 = women. CVD = cardiovascular disease, HW = homework. Achievement a composite of desire to learn and mastery scales from the Motivational Trait Questionnaire (MTQ). Anxiety a composite of worry and emotionality scales from the MTQ.

Table 21

Correlations of measures included in the path analysis for technology/xerography.

Measure	*1.*	*2.*	*3.*	*4.*	*5.*	*6.*	*7.*	*8.*	*9.*	*10.*	*11.*	*12.*
1. Age	1											
2. Gc	-.16*	1										
3. Gf	-.42**	.76**	1									
4. Gender	-.01	.01	-.03	1								
5. Technology Experience	-.17*	.24**	.33**	-.10	1							
6. Tech/Xerog. Prior Knowledge	-.13	.75**	.75**	-.13	.45**	1						
7. Technology Interests	.02	-.08	.00	-.11	.38**	.09	1					
8. Xerography Post-video	-.27**	.77**	.74**	-.03	.34**	.75**	.02	1				
9. Xerography Post-HW	.01	.64**	.57**	-.03	.26**	.72**	.09	.67**	1			
10. Achievement	-.01	-.02	.03	-.03	.26**	-.04	.26**	-.06	-.10	1		
11. Anxiety	-.17*	.09	.16*	.09	.02	.11	-.15*	.11	.08	-.24**	1	
12. Xerography Learning Goals	.13	-.19**	-.19**	-.19**	.14*	-.04	.29**	-.19**	-.04	.16*	-.15*	1

Note. * $p < .05$, ** $p < .01$. Gc = crystallized intelligence, Gf = fluid intelligence. Gender coded as 1 = men and 2 = women. HW = homework. Xerog. = xerography. Achievement a composite of desire to learn and mastery scales from the Motivational Trait Questionnaire (MTQ). Anxiety a composite of worry and emotionality scales from the MTQ.

The hypothesized model was tested for both domain/topic areas and the results are shown in Figure 4. Path coefficients for health/CVD are shown on top; coefficients for technology/xerography are on the bottom. It is interesting to note that the relationship between age and Gc is positive in the models (.19) as opposed to the negative zero-order correlation reported earlier. This reversal of signs can be seen as a function of a suppression effect and as an endorsement for simultaneous estimation of the relationships among variables (i.e., path modeling). That is, the strong relationship (or collinearity) between Gf and Gc influenced the correlation between age and Gc. When the effect of Gf was partialled out in the path model, the relationship between age and Gc was positive. A similar pattern of results can be observed for Health Experience and Health Domain Knowledge (a non-significant zero-order correlation, yet a significant path coefficient).

Model fit for both models was poor: CVD, $\chi^2(48, N = 199) = 225.13$, RMSEA = .13, CFI = .81; Xerography χ^2 (48, N=199) = 219.10, RMSEA = .13, CFI = .83. Alternative models that were a priori hypothesized were then tested. For each alternative model, a χ^2 difference test was used to determine whether the alternative model fit was significantly better than the original model (as described above). First, a direct relationship was included from age to prior knowledge for both models. The χ^2 difference test revealed that this path was significant for the CVD domain only $\chi^2(1, N=199) = 34.32, p < .001$. For Technology, including this path did not significantly improve the fit of the model $\chi^2(1, N=199) = 1.25$, *ns*. Second, a direct relationship was tested between gender and performance on the video knowledge post-test and homework knowledge post-test for both models. These paths were not significant for either model:

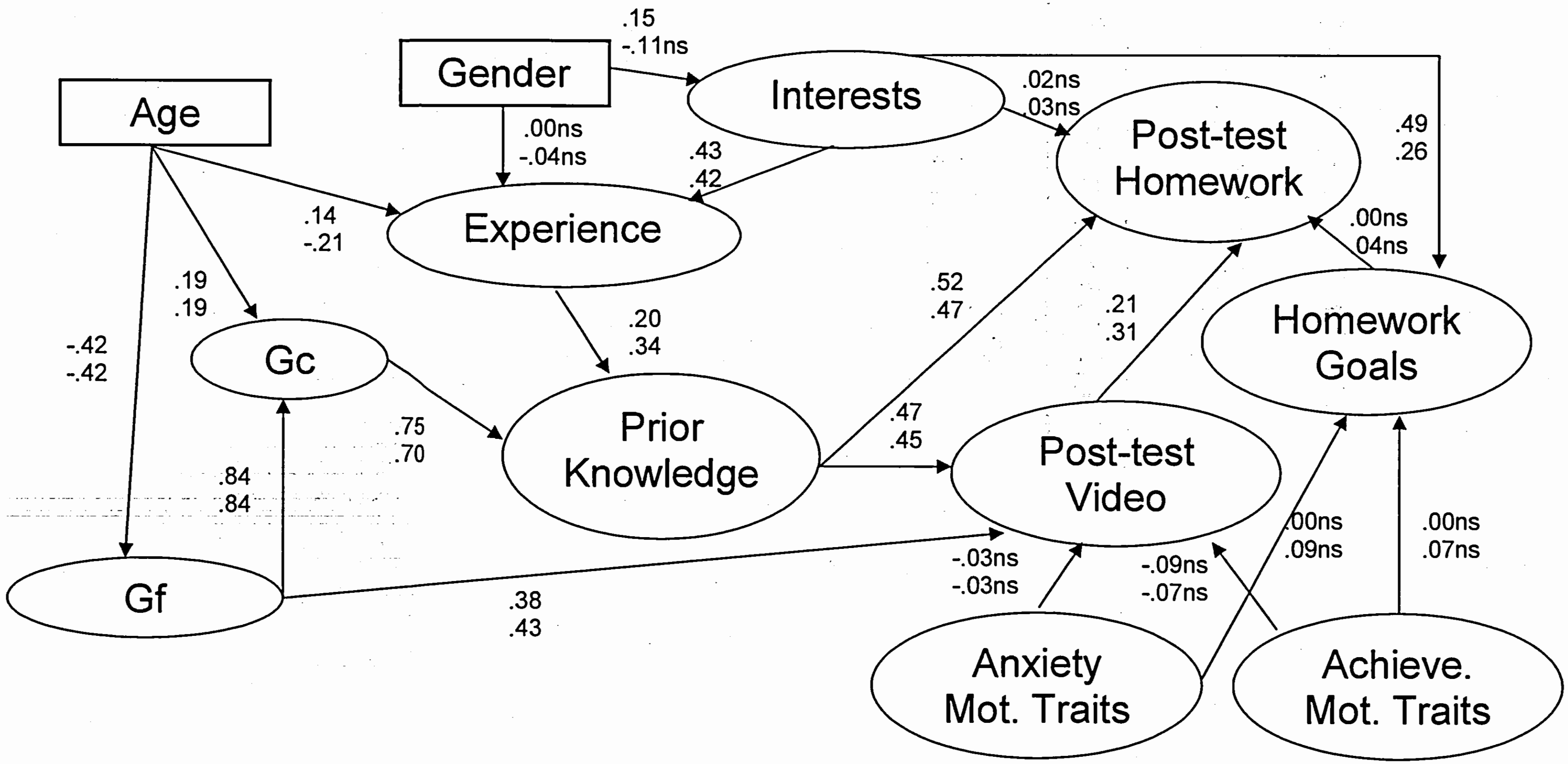

Figure 4. Test of hypothesized model for CVD and xerography. Path coefficients for CVD are on top; path coefficients for xerography are on the bottom. Gf = fluid intelligence; Gc = crystallized intelligence; Mot. = motivational; Achieve = achievement. Non-significant paths marked ns.

gender to CVD video post-test $\chi^2(1, N=199) = .05$, *ns*; gender to CVD homework post-test $\chi^2(1, N=199) = 2.5$, *ns*; gender to xerography video post-test $\chi^2(1, N=199) = 1.1$, *ns*; gender to xerography homework post-test $\chi^2(1, N=199) = .68$, *ns*. Third, direct relationships were tested between the anxiety and achievement motivational traits and the homework post-test for both topic areas. This path was significant only for anxiety motivational traits and post-homework performance for CVD, $\chi^2(1, N=199) = 6.2, p < .05$. It was not significant for achievement motivational traits and homework post-test performance for CVD, $\chi^2(1, N=199) = .11$, *ns*, or for anxiety or achievement motivational traits and xerography, $\chi^2(1, N=199) = .02$, *ns* and $\chi^2(1, N=199) = 2.21$, *ns*. The significant direct path from anxiety motivational traits to post-test performance for the CVD homework module was small and positive (.13), indicating again that worry was positively related to performance on this quiz.

Because of the poor fit of the model even after a priori specified alternative models had been examined, a more exploratory, post-hoc analysis was conducted to identify the source of model misspecification. This post-hoc analysis included two steps. First, a streamlined model, including only age, ability, domain knowledge, post-test video, and post-test homework knowledge was tested for both domains. Non-ability measures were excluded from this part of the analysis to simplify the model. Gender was not included because it failed to show significant relationships with the main constructs of interest in the model. Initial fit of this streamlined model was also inadequate for both domains: CVD, $\chi^2(7, N=199) = 33.90, p < .05$, RMSEA = .14, CFI = .96; Xerography, $\chi^2(7, N= 199)= 93.28, p < .05$, RMSEA = .25, CFI = .90. For health/CVD, examination of the modification indices showed that model fit could be improved if a direct path were allowed from Gc to homework post-test performance and from Gc to video post-test performance. Theoretically, these paths made post-hoc sense in terms of a more direct relationship between knowledge acquisition and Gc, and they were allowed. Fit for the modified streamlined model for health was good, χ^2 (5, N=199) = 10.41, *ns*, RMSEA = .07, CFI = .99. For the Technology/Xerography domain, modification indices showed that model fit would be improved by allowing a direct path from Gc to video post-test performance (similar to the health/CVD model described above), a direct path from Gf to domain knowledge, and interestingly, a direct path from Age to homework post-test performance. The direct relationship from Gc to video post-test performance (as in the health/CVD domain) indicates that the effect of Gc on knowledge acquisition from the video is not entirely mediated by prior domain knowledge. The direct relationship of Gf to domain knowledge in this highly technical domain was aligned with results of previous research, which found a strong relationship between knowledge of technology and Gf (Ackerman et al., 2001). The direct positive relationship between age and post-homework test performance is interesting in part because the zero-order correlation between these two variables as reported in earlier was negligible. However, in the model, the negative relationship between Gf and age is partialled out of the relationship with age and other variables in the model. Thus, there appears to be some positive influence of age on post-homework performance. This influence could be driven by other non-ability measures that were not used here (i.e., willingness to follow the instructions of the study and read through the homework material). Fit of the streamlined, modified model for Technology/Xerography was excellent, χ^2 (4, N = 199) = 6.01, *ns*, RMSEA = .05. CFI = 1.0.

A subset of the non-ability measures was then added to the streamlined models. Because the motivational traits and learning goals did not show any significant relationship with the other variables in the model, they were not considered further. The model for Health/CVD is shown in Figure 5 and the model for Technology/Xerography is shown in Figure 6. Fit of these models was adequate to good; Health/CVD, χ^2 (14, N = 199) = 40.95, $p < .05$, RMSEA = .09, CFI = .97; Technology/Xerography, χ^2 (13)= 39.82, $p < .05$, RMSEA = .09, CFI = .97.

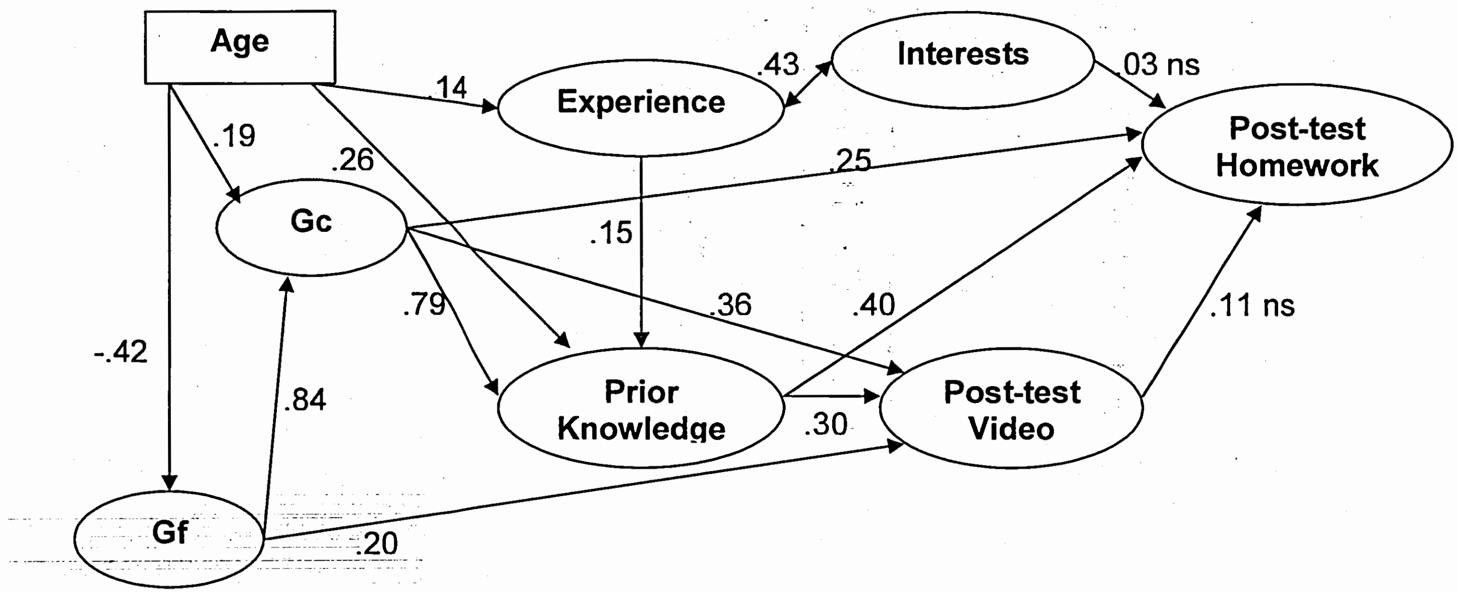

Figure 5. Revised model for health/CVD (not including gender, motivational traits, or learning goals). Gf = fluid intelligence, Gc = crystallized intelligence. ns = not significant.

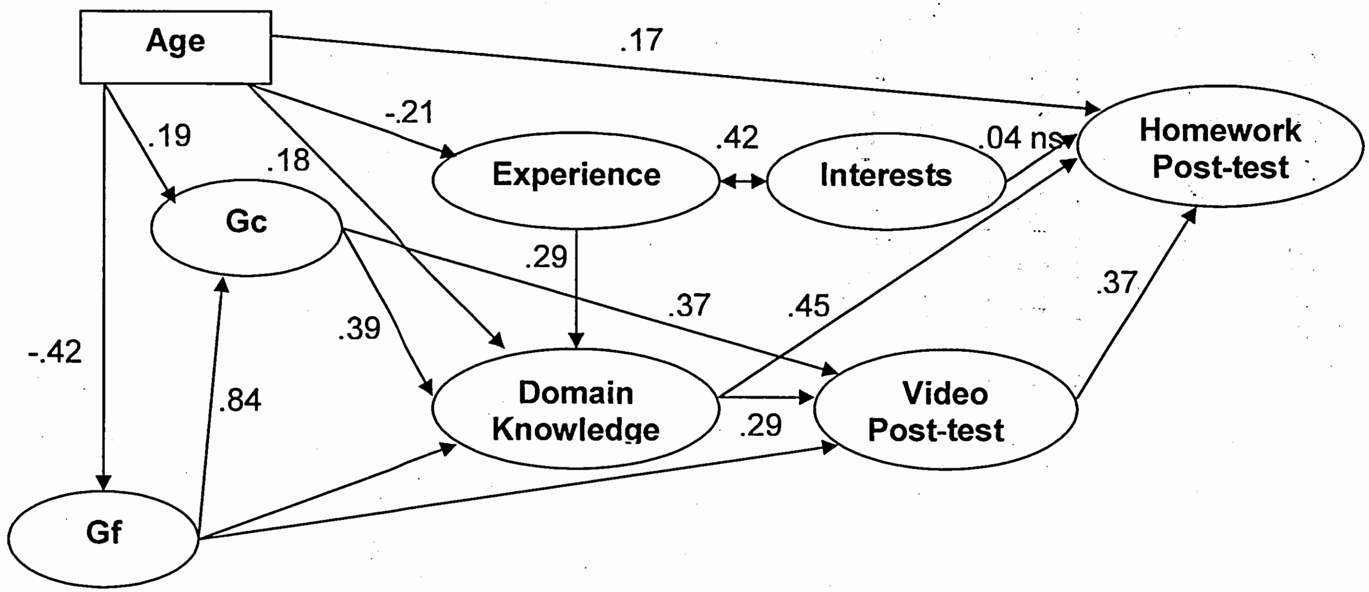

Figure 6. Revised model for technology/xerography (not including gender, motivational traits, or learning goals). Gf = fluid intelligence, Gc = crystallized intelligence. ns = not significant.

Hypothesis Testing

The models described above will be used to examine Hypotheses 1 through 8 below. Hypothesis 1 was that prior knowledge would be directly related to post-test knowledge for both the homework and video learning and that there would be a large effect of prior knowledge. This hypothesis was supported for both domain/topic areas. Zero-order correlations between prior knowledge/domain knowledge and post-tests for the video and homework ranged from $r = .55$ to .78. Also, path coefficients from domain knowledge to post-test performance for the video and homework are similar for health/CVD and for technology/xerography.

Hypothesis 2 was that Gf would be directly related to post-video performance. This hypothesis was also supported for both domains, and results were similar across domains. Furthermore, Gf did not show a direct relationship with post-test performance for homework learning in either domain, suggesting that Gf was more directly relevant in learning in the more constrained environment, as hypothesized. However, this hypothesis was also partly based on the notion that Gf would be more important than Gc in predicting post-test performance for the video (i.e., no direct path from Gc to post-test performance for the video was hypothesized). Examination of the final modified models indicates that this was not the case. That is, Gc had a direct relationship to knowledge acquisition for the video module for both domains – and that Gc was more important for learning for both types of environments than had originally been hypothesized.

Hypothesis 3 was that Gf would be indirectly related to post-test performance for the homework and that the effect of Gf on homework post-test performance would be mediated by Gc and domain knowledge. As can be seen in Figures 5 and 6, this hypothesis was generally supported. As hypothesized, Gf was indirectly related to post-test performance for the homework and its influence was mediated by Gc, prior knowledge, and post-test performance on the video for the Health/CVD model. For the Technology/Xerography model, the relationship between Gf and post-test performance for homework was not direct, and was similar to the relationships shown in the health/CVD model. However, a direct relationship was found between Gf and prior knowledge for technology/xerography, indicating a more direct relationship between Gf and post-test performance for technology.

Hypothesis 4 was that interests would be directly related to performance on the post-test for the homework learning experience. This hypothesis was not supported. Interests had a negligible relationship with all domain knowledge assessed in this study. However, interests were related to self-reported experiences in the domain for both domains, providing some convergent validity for these measures.

Hypothesis 5 was that experiences would be indirectly related to performance on the post-tests for both video and homework learning and that the influence of experiences would be mediated by domain knowledge. As can be seen in the figures, this hypothesis was supported for both domains although the relationship was stronger for Technology/Xerography relative to Health/CVD (path coefficients of .29 and .15 respectively).

Hypotheses 6 and 7 were about the relationship between motivational traits, learning goals, and knowledge acquisition. Specifically, Hypothesis 6 was that anxiety and achievement oriented motivation traits would be directly related to post-test performance for video learning. Hypothesis 7 was that learning oriented motivational traits would be indirectly related to post-test performance for homework learning and that the relationship would be mediated by performance goals. These hypotheses were not supported. The achievement and anxiety traits as well as the learning goals failed to show any significant relationship with existing knowledge or knowledge acquired for video or homework learning across both domains.

Hypothesis 8 was that the relationship between age and post-test performance for the homework would be mediated by interests, experience and domain knowledge. This hypothesis was partly supported. In the health/CVD domain, the effect of age on learning was mediated by experience and domain knowledge. The relationship between age and experience and the relationship between age and domain knowledge were both positive and significant in this model. For the technology/xerography domain, the relationship between age, experience and learning is not as clear. Contrary to prediction, age was negatively related to experience with technology. However, the path from age to domain knowledge is small but significant and positive suggesting that part of the influence of age on post-test performance was mediated by domain knowledge and Gc. Also, there is a direct effect of age on post-test performance on the homework test in this domain. As discussed earlier, this could be a result of the partialling of the negative relationship between Gf and age and may be a function of additional non-ability measures that could have influenced post-test performance for homework learning.

CHAPTER 6

DISCUSSION

I set out to identify predictors of knowledge *acquisition* within the framework provided by the PPIK theory (Ackerman, 1996) by examining ability and non-ability constructs such as motivational traits, interests, experiences as well as age and gender across two different knowledge domains. Even though the study was conducted in a laboratory setting, an attempt was made to construct educational modules that had real-world relevance (e.g., in the domains of health/CVD and technology/xerography) and to conduct learning experiences that resembled learning experiences encountered in daily life (e.g., structured training with an opportunity for investigation of the topic on one's own). The results of the study are decidedly mixed. While the hypotheses regarding the role of prior knowledge and ability were generally supported, and there was also evidence for the importance of experience for knowledge acquisition, the findings of little or no relationship between knowledge acquisition and the non-ability traits assessed in this study (i.e., self-set learning goals, motivational traits, interest in the domain or topic area) are disappointing.

The interest measures used here were designed for this study and specifically aligned with the knowledge assessed (as opposed to broader measures of occupational interest such as Holland's themes, 1959). It was originally thought that matching the breadth and content of the interest measures to the criterion would result in a higher correlation between them (i.e., Brunswik Symmetry; Wittmann & Süβ, 1999). However, the design of these measures may also be one reason why I failed to find any significant relationship with knowledge acquisition. That is, the breadth and content of the interest measures may have been too narrow and may have missed relevant aspects of the construct that would have better predicted knowledge acquisition.

The significant negative correlations between interest in CVD and knowledge about CVD were also troubling, as they indicated that those who had more knowledge were actually less interested in the topic. In retrospect, however, this relationship appears to be a function of the domain of health/CVD. That is, individuals may have experience and acquire knowledge in this area mainly because they are required to do so (e.g., because of a medical condition or to stave off death) than because they are intrinsically interested in the topic. In this sense, "interest" may not be the appropriate construct to measure – that is, one might be as interested in CVD as in household chores, but they may be required to know about it. Rather, it may be, and the results of this study suggest, that experience is perhaps a better construct to examine for knowledge acquisition in this type of domain (i.e., in domains that could be classified as "obligatory" knowledge for a certain level of survival).

Experience was one non-ability measure that showed consistent significant positive relations with prior knowledge in this study. One reason for this might be that the biodata measures were relatively more objective than the other self-report measures used. As a result, they were perhaps less susceptible to demand characteristics or self-presentation bias (e.g., see Nickels, 1994) – factors that may have affected responses on the interest, motivational trait, and self-set goal measures.

Additionally, objective measures of note-taking were used in this study. These measures were originally thought of as additional indicators of interest in the domain.

However, scores on the notes pages were unrelated to the interest measures used here. Rather than a surrogate for interests, the notes pages seemed to be more an indicator of engagement in the learning activity (as evidenced by their correlation with knowledge acquisition). This engagement could be due to interest in the topic or domain, or many other factors. The significant positive correlation with gender and note taking suggests that it may be somewhat related to personality variables more associated with women such as a more traditional/conventional or conscientious learning style (Ackerman et al., 2002). Unfortunately, these measures were not included in this study and thus this speculation cannot be further examined. Note taking (at least for video learning) was also positively correlated with both Gf and Gc, suggesting that those with higher ability do employ strategies for learning (as opposed to thinking they are smart enough to remember the material without taking notes).

It is interesting to consider what was gained by examining two different knowledge domains and to summarize the findings by contrasting the two domains. First, the similarities in the results between two very different domains are striking, suggesting that a similar set of predictors (i.e., ability, prior knowledge, experience) would be pertinent for predicting learning across a wide range of topic areas. The differences in the domains are also interesting to examine. For example, the relationship between age and learning was different across domains but suggests that experience is important for learning and knowledge acquisition in both domains – that is, older individuals are likely to have more experience with health and younger individuals (especially those growing up with the Internet) are likely to have more experience with technology.

As has been found by other researchers (Chiesi et al., 1979; Hambrick & Engle, 2002; Walker, 1987), this study demonstrated that prior knowledge was an important and significant predictor of knowledge acquisition for learning from the video and from the homework for both topic areas examined. Further, prior knowledge was somewhat more important for learning in a less constrained learning environment (i.e., the homework module) than for learning in a more constrained learning environment (i.e. the video module). This supports the notion that knowledge acquired is indeed more aligned with more typical performance than it is with maximal performance (i.e., performance in a "do your best" situation; Ackerman, 1994; Cronbach, 1990).

Examination of the ability measures and their relation with knowledge also revealed differences between the two learning experiences. Gf had a direct effect on learning from the video modules for both domains and an indirect effect on learning from the homework. This suggests that video learning required more focus of direct attention and application of memory and reasoning ability than did learning from the homework – again reinforcing the difference between a more typical and maximal performance situation.

The findings regarding Gc in this study show that the role of Gc in knowledge acquisition was initially underestimated. Although hypothesized to have an indirect relationship on knowledge acquisition (through prior domain knowledge only), post-hoc analyses revealed direct relationships between Gc and learning from the video for both topics. Gc also had a direct relationship with learning from the homework in the domain of health/CVD. It is appropriate to ask why the effect of Gc was not fully mediated through domain knowledge when one might consider Gc to be a more general (and perhaps less relevant) measure of crystallized ability than the measures of prior knowledge used in this study. One reason might be that, even though measures of Gc may be less relevant than measures of prior knowledge, scores on these tests can be considered a general indicator of success acquiring knowledge throughout the lifespan. Thus, it may be that those who are higher in Gc are more adept at knowledge acquisition, regardless of domain or learning environment. This suggests the existence of a Matthew effect (Stanovich, 1986) or cumulative benefit (i.e., "rich get richer" scenario) for knowledge acquisition.

Limitations of the study

This study also has some limitations that are worth noting. First, although comparing the results of the video learning module with the homework learning module suggests definite differences in the relationships between predictors and criteria for these two modules, no conclusions can be stated about these differences because the study reported here was not a highly controlled experiment. To conclude that a difference in the level of constraint of the learning environment produced differences in the relations between the ability and prior knowledge measures and learning in this study, an experiment holding all variables constant except for the constraint of the learning environment would need to be conducted. This would be an interesting study, but was not the goal of the study reported here. Rather, the goal was to examine knowledge acquisition in a more real-world environment than has been done previously in the experimental domain -- across two different environments to mirror what generally happens in educational or vocational setting (i.e., a structured educational module followed by independent study).

It is perhaps also dangerous to directly compare across the domain/topic areas included in this study for conclusive results. While an effort was made to equate these two domains and learning modules for difficulty, the knowledge scales used to assess knowledge acquisition are, in general, incommensurable. To have absolute parity between these two domains, a more thorough item response analysis would need to be conducted. Even with this type of analysis, it would be difficult to assess the difference in the difficulty of the knowledge tests from these real-world knowledge domains. This is because the difficulty of the tests would depend somewhat on the level of prior knowledge possessed by study participants (e.g., as opposed to the study of trigrams – where prior knowledge can be controlled). These limitations are also, in some way a consequence of other strengths of the study. What was given up in experimental control, was perhaps gained in the generalizability of the results to educational and vocational training situations.

The homework module was included in this study as a function of the negligible relations found between non-ability traits and learning from a video in pilot testing (i.e., it was thought that a less constrained learning environment would allow the emergence of non-ability traits for predicting learning). Although learning from homework may have been a more reflective of a typical learning environment relative to learning from the video (as evidenced by the relations between Gf/Gc, and prior knowledge), the non-ability traits included in this study did not correlate with performance on homework learning as hypothesized. It may indeed be the case that interests and non-ability traits have absolutely no relationship to knowledge acquisition – but prior research on predicting domain knowledge (Alexander, Jetton, & Kulikowich, 1995; Reeve & Hakel,

2001) make this conclusion untenable. Another possibility is that, even though the homework learning experience was more of a typical learning experience than the video, it was still fairly constrained. That is, individuals had only 72 hrs to examine the packet of information, and participants may have felt restricted in some way by the parameters of their participation in the study. In other words, it may be that the homework environment, while not as constrained as the video environment, was not natural enough reflect how individuals may apply their motivation, interests and experiences to acquire knowledge. That said, it is difficult to think about a learning environment within a work or educational setting that does not have certain parameters or restrictions, in terms of mandating the topics or materials to be learned, and enforcing deadlines. As such, the homework learning environment used in this study may be more generalizable to education and work settings than not. In any event, the role of the non-ability traits used in this study and knowledge acquisition is unclear.

Another related limitation of the study is that a measure of environmental constraint (whether subjective or objective) was not used. There are two reasons why it was not. First, an existing measure was not identified before this study was conducted. Second, it was feared that subjects would not be able to report on their subjective relative constraint in either learning environment – given the general constraints involved in participating in a study. In retrospect, a subjective measure of environmental constraint would have been an appropriate manipulation check and may have provided some additional insight into the participant's reactions to the learning environment.

Conclusions

It is appropriate, perhaps especially in a dissertation, to answer the question, Why are these results important? As discussed above, experimental research has already identified prior knowledge and ability as important predictors of knowledge acquisition. However, the domains examined in many of these experimental studies have been invented or obscure (e.g., learning nonsense syllables, learning about fictitious baseball games). This study examined ecologically valid domains and found that the relations between ability, prior knowledge, and knowledge acquisition can actually change as a function of the knowledge domain. In addition, this study examined knowledge acquisition across a learning process (i.e., a more constrained learning environment followed by a more self-paced learning environment) and found that the predictors of learning also change as a function of where an individual is in that process (i.e., as a function of environment).

The study reported here was also based on the PPIK theory and thus examined ability, prior knowledge, and non-ability traits in knowledge acquisition. Even though the results pertinent to the study of the personality and interest measures were disappointing, an important attempt was made to broaden the set of predictors to include ability and non-ability components. This study was not successful in identifying what many of these predictors might be, but did identify experience in a domain and age as relevant to knowledge acquisition for the two domains examined here. These findings, although perhaps not as robust as originally intended, are still an important step in expanding the set of predictors used to examine the potential for learning.

Most importantly perhaps, the importance of Gc and prior knowledge in knowledge acquisition shown in this study provides support for the notion that a narrow conceptualization of intelligence that includes mainly reasoning ability or memory may not only miss a large portion of what adults know (Ackerman, 2000), but would also potentially underestimate what adults can *learn*. This study suggests that if measures used in selection for education and work settings are too focused on raw reasoning ability or memory, they may eliminate potentially good candidates (i.e., those that have capacity for performance *and learning*) from consideration. Furthermore, the importance of Gc in this analysis (over and above domain knowledge for predicting learning outcomes) suggests, that for some domains, a more general test of knowledge could be useful for selection purposes. This could be important news for industrial/organizational psychologists who are interested in selection and intrigued by the importance of job knowledge for predicting performance (e.g., Schmidt & Hunter, 1998), but who are unable to conceptualize of a measure of job knowledge that would be appropriate to give potential job candidates (as opposed to incumbents). It may be that for many domains and jobs, a test of more general knowledge would meet this need.

APPENDIX

Instructions for Homework

For this part of the study, you will be helping evaluate how much people can learn from material studied independently on two topics: (1) heart disease, and (2) duplicating technology. You have been provided with two folders; the red folder contains information on heart disease and the blue folder contains information on duplicating technology. Each folder includes a variety of articles and blank notes pages. Because we will be using these folders in future studies, **we ask that you do not write or highlight on the articles, but rather use the notes pages provided to take notes**. Please bring the folders and articles back to the Knowledge and Skill lab when you return for your next scheduled session.

As you study the material in these folders, please focus on anything that seems interesting to you. In fact, we encourage you to spend time on articles and topics that you find interesting and to seek out additional information on these topics if the articles do not satisfy your interests. At the beginning of your next session, you will be given a quiz on the information in these folders. Unlike the quiz following the video, you will not be provided extra study time before the quiz is administered.

If you have any questions while reading these materials, please call the Knowledge and Skill Laboratory at 404-385-0157.

Thank you for your participation in the study.

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