THE INFLUENCE OF PHYSICAL HEALTH AND OCCUPATIONAL COMPLEXITY ON COGNITIVE PERFORMANCE IN ADULTHOOD

by

Brent John Small
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M.A., University of Victoria, 1992

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We accept this dissertation as conforming to the required standard

Dr. David F. Hultsch, Supervisor (Department of Psychology)

Dr. Roger A. Dixon, Departmental Member (Department of Psychology)

Dr. D. Stephen Lindsay, Departmental Member (Department of Psychology)

Dr. W. John Walsh, Outside Member
(Department of Psychological Foundations, Faculty of Education)

Dr. Tannis Y. Arbuckle, External Examiner
(Department of Psychology and Center for Research in Human Development, Concordia University)

University of Victoria

Supervisor: Dr. David F. Hultsch

ABSTRACT

This study examined the role of physical health and occupational complexity in predicting cognitive performance. The sample consisted of 12,622 adults (5,852 men and 6,770 women) between the ages of 23 and 85 years (M= 55.6 years). The data were collected as part of the Health and Retirement Survey, a study designed to investigate issues related to retirement and aging in a United States population-representative sample. Physical health was measured by both self-report and objective indices. Specifically, self-ratings of current and retrospective health, as well as number of illness episodes, difficulties with activities of daily living, and incidence of chronic illness were assessed. Vital capacity and grip strength represented the objective measures of health status that were measured. In addition, participants answered questions regarding the types of occupational demands faced in the workplace. Specifically, questions were directed at the extent of physical and mental demands of work, as well as the extent to which the job required individuals to analyze data, and the amount of freedom individuals possessed in deciding how work tasks were accomplished. Three measures of cognitive performance were used as the outcome measures: Immediate and delayed word recall and the WAIS-R subtest word similarities.

Results indicated that very little variance in cognitive performance was predicted by either self-report or objective indices of health status. Self-ratings of current health, presence of high blood pressure, and incidence of chronic illness predicted, on average, 1% of performance in abstract reasoning. Paradoxically, more chronic illness was weakly related to improved reasoning performance. The paucity of significant results may be related to the nature of the cognitive outcome tasks that were used.

Measures of occupational complexity predicted significant portions of variance, ranging from 7% to 12%, in abstract reasoning performance. Specifically, occupations that allowed employees to make decisions regarding how work was done were associated with better reasoning scores. Results from both self-ratings and standardized measures of occupational complexity indicated that the types of demands (e.g., physical or mental) are not as important as the latitude that is afforded in deciding how work is done. However, results from an analysis of unemployed participants suggests that the relationship between occupational complexity and cognitive performance may be complicated by factors related to educational selection of the sample.

Examiners:

Dr. David F. Hultsch, Supervisor (Department of Psychology)

Dr. Roger A. Dixon, Departmental Member (Department of Psychology)

Dr. D. Stephen Lindsay, Departmental Member (Department of Psychology)

Dr. W. John Walsh, Outside Member (Department of Psychological Foundations, Faculty of Education)

Dr. Tannis Y. Arbuckle, External Examiner (Department of Psychology and Center for Research in Human Development, Concordia University)

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Dedication

To my parents, Aileen and Bob Small.

Chapter I

INTRODUCTION

In recent years, psychologists have evinced increased interest in the role that non-cognitive variables play in determining memory and intellectual abilities. Typically, variables such as self-rated health and occupation are viewed as status variables. They allow us to describe the sample in terms of whether the participants are relatively healthy or not, and also whether they occupy blue or white collar occupations. Recently, however, these same variables have gained prominence as potential determinants of intellectual performance. The role these variables play in affecting cognitive performance is both of methodological and practical importance. Methodologically, it would imply that these variables cannot simply be treated as status variables. Because of their potential to influence cognitive performance, they should routinely be assessed and treated as potential confounds in the study of cognitive performance. Practically, health status and environmental complexity may elucidate means to ameliorate individual's cognitive skills. Individuals may be encouraged to improve their health or become more actively engaged with their environments in order to increase their functional capacity.

Several studies have assessed the role that physical health plays in predicting cognitive performance. It is clear that substantial levels of chronic disease result in significant decrements in cognitive functioning (see Elias, Elias, & Elias, 1990; Siegler & Costa, 1985 for reviews). Cardiopulmonary and cerebrovascular disease, in particular, appear to be associated with decrements in performance (Barrett & Watkins, 1986; Hertzog, Schaie, & Gribbin, 1978; Speith, 1965). In addition, studies that have assessed physical health by means of self-reports have indicated that self-rated physical health is an important predictor of cognitive functioning. For example, Perlmutter and Nyquist (1990) found significant relationships between verbal intelligence and self-rated health. Similarly, Hultsch, Hammer, and Small (1993) reported that self-rated health accounted for statistically significant portions of variance in measures of verbal speed, working memory, and text recall. However, Salthouse, Kausler, and Saults (1990) and Arbuckle, Gold, and Andres (1986) found few modifications in the cognitive performance of healthy adults as a function of controlling for self-rated health. These inconsistencies may be related to how adequately health is dimensionalized, as well as the demographic composition of the samples. For example, age, education, and gender, as well as personality characteristics such as neuroticism and depression, have been shown to be related to self-report measures of physical health (Costa & McCrae, 1985; Elias, Robbins, Blow, Rice, & Edgecomb, 1982; Hultsch et al., 1993). Therefore, studies that use self-report measures of health must take these variables into account.

Another class of variables that has recently garnered attention as potential determinants of cognitive performance are measures of environmental complexity. This includes how active individuals' lifestyles are, as well as how complex their work environment is. For example, Hultsch et al. (1993) found that cognitive performance is related to participation in complex, cognitively, demanding activities, and that this relationship appears to become stronger with increasing age. Similar results have been reported by Arbuckle et al. (1986) and Craik, Byrd, and Swanson

(1987). A related line of research has examined the role that occupational complexity plays in predicting cognitive performance. Several studies (Avolio & Waldman, 1990, 1994; Kohn & Schooler, 1973, 1978; Small & Hultsch, 1993) have demonstrated that occupational characteristics are important predictors of cognitive performance. Specifically, occupations that provide the opportunity to use thought, initiative, and independent judgment have been found to be positively related to performance on cognitive tests.

The present study examined the role of health status and occupational characteristics on cognitive performance. In a series of structural equation models, the influence of physical health, indicated by both self-report and objectively measured indices, on word recall and reasoning was examined. Similarly, multiple self-rated, and standardized ratings, of aspects of an individual's work environment were examined to determine their role in affecting cognitive performance.

Further, this study provides the unique opportunity to study these relationships in a population-representative sample. One difficulty in studying the relationship between health status, occupational complexity, and cognitive performance is the nature of the samples that are used. The samples used to assess these relationships are typically comprised of well-educated and healthy individuals. It may be the case that the relatively weak, or nonexistent, relationships that are observed between health status, occupational complexity, and cognitive performance are related to the limited variability of the independent variables. In the present study, a population-representative sample of adults was used to test the relationship between health status, occupational complexity, and cognitive performance. It was expected that such a diverse sample would increase the variability of the health conditions and occupations that are observed, as well increase the generalizability of the results.

Chapter II

REVIEW OF THE LITERATURE

The present chapter discusses literature relevant to the present study. First, the theoretical perspective that guided the research is introduced. Next, work pertaining to the influence of health status, both measured objectively and by self-reports, on cognitive performance will be examined. The subsequent section focuses on several studies that have investigated the relationship between environmental complexity and cognition. Next, a brief review of the major analytical tool used in the present study, structural equation modeling, will be presented. Finally, the design and the hypotheses that guided the research will be outlined.

Theoretical Perspective

The present research is guided by a contextual view of human aging. Aging is a developmental process that reflects not only the biological changes that take place over the life span, but also the environmental contexts in which those changes occur. Researchers who study aging from this perspective (e.g., Baltes, 1987; Schaie, 1983) view development as resulting from the lifelong interaction between changes within the individual and the demands and supports provided by the environment. Baltes (1987) has identified three types of influences that effect an individuals' development: Age-graded influences, history-graded influences, and nonnormative influences. These three sources of influence operate throughout the life span, and Baltes argues "are responsible for how lives develop" (p. 621). Age-graded influences are those that have a fairly strong relation to chronological age. Examples of these include biological maturation and health status. History-graded influences are those that are associated with historical time. These include changes in characteristics of successive cohorts (e.g., educational practices) as well as period-specific events (e.g., war, economic depression). Finally, nonnormative influences are more idiosyncratic in nature. They contribute to the individuality of development, and are not related to specific age or time periods. In the present study, the effect of two of the three influences on development is assessed. Specifically, the effect of the "age-graded" influence of physical health status, as well as the "non-normative" influence of occupational complexity on individual cognitive performance is examined.

Adoption of a contextualist position implies that it is necessary to take into consideration the individual characteristics and life experiences that an individual brings to the situation. In the memory literature, Jenkins (1974, 1979) provided one of the earliest, and most comprehensive, contextual views of memory performance. He argued that full understanding of memory performance requires consideration of four major sources of variation: Acquisition variables (e.g., attention, strategies, level of encoding, elaboration), materials (e.g., modality, organization structure, conceptual difficulty, richness of features), test variables (e.g., quality and quantity of retrieval information, specificity of transfer), and subject-related variables (e.g., preexperimental knowledge, skill, motivation, interests). Moreover, the interactions among the four aspects of variation must also be taken into account when evaluating a particular subject's level of memory performance.

The importance of age-graded influences, such as health status, or nonnormative influences, such as occupational complexity, in influencing cognitive performance is not a view that is held by all. For example, researchers who study aging from an experimental perspective (e.g., Salthouse, 1987, 1991) might argue that the modifications in performance that result from differences in health, education, or social structure are less important than the identification of universal mechanisms of change in memory performance across individuals. Indeed, in his 1991 book, Theoretical Perspectives on Cognitive Aging, Salthouse characterized health status as an "artifactual interpretation" of cognitive aging. While he acknowledged that some variations in cognitive performance result from differences in health status, he stated that, "age-related declines in health status are not responsible for most of the age-related declines in cognitive functioning observed among adults recruited from samples of convenience" (p. 67). In general, investigators with an experimental perspective seek to identify cross-individual similarities in changes in cognitive abilities (Dixon & Hertzog, in press). For example, research from an experimental perspective has sought to identify a small set of processing resources that are presumed responsible for much of the negative changes in memory performance across age groups.

By contrasting the two perspectives, we can see the differences in how the importance of health status, or any other nonnormative influence, is treated. From an experimental perspective, the importance of potential explanatory variables is gauged by their ability to account for much of the age-related variance in cognitive performance. On the other hand, from a contextual perspective the influence of variables such as health status and environmental complexity are treated as a component, and perhaps a small component, of overall cognitive performance. It is the contextual approach to cognitive aging that is adopted in the present study.

Physical Health and Cognitive Performance

Gerontologists have suggested for many years that it is important to discriminate changes in cognitive functioning that are related to intrinsic maturational processes from those that are attributable to various disease processes (Birren, 1965; Busse, 1969). Indeed, Busse (1969) has argued for the distinction between primary aging, the inherent normal changes that occur with age, and secondary aging, the changes that result from illnesses that accompany aging. Recently, Baltes and Baltes (1990) suggested a tripartite conceptualization of aging: Normal, sick (pathological), and optimal aging. Normal aging is the process that is dominant within a society and is represented by individuals who are not suffering from manifest illness. It is aging without major biological or mental pathology. This contrasts with pathological aging, which is characterized as aging that is accompanied by medical etiology or syndromes of illness. For example, individuals who suffer from Alzheimer's disease are undergoing a pathological aging process. Optimal aging refers to a utopian condition in which, "aging is under development-enhancing and age-friendly environmental conditions" (Baltes & Baltes, 1990, p. 8).

In the present study, aging is conceptualized as primary aging, as defined by Busse (1969), or a mixture of Baltes and Baltes's (1990) normal and pathological aging. It is acknowledged that many individuals grow older without experiencing major pathological conditions such as Alzheimer's disease. However, it is also clear that the incidence of health-related disorders is positively correlated with age (Siegler, 1990). Therefore, the type of aging that is of interest in the present study is that in which some level of health pathology is involved, but it is not so extreme as to cause functional disability.

Although changes in health status are thought to affect cognitive performance, they may not affect all abilities equally. Perlmutter (1988) argues that changes to the "biological substrate" only affect basic mechanisms of cognition or fluid abilities, such as working memory or processing speed. On the other hand, changes in health status would not affect more crystallized abilities, such as vocabulary or world knowledge. Perlmutter bases these predictions on her three-tier model of cognition. The first tier, characterized by fluid abilities, consists of the most primitive abilities, which are assumed to reflect biological processes. This system is available from birth and intraindividual variability is thought to reflect genetic variability across individuals. These abilities are thought to be dependant on the integrity of the underlying biological substrate. As such, changes in health status, for example, would affect these process[illegible] The second tier is characterized by crystallized abilities, such as vocabulary or semantic knowledge. This tier develops as a result of experiences with the external environment. The experiences that influence development of this tier are both those that are common across individuals (history-graded influences), as well as experiences that are unique to the individual (nonnormative influences). This tier emerges later in life and is thought to be relatively immune to deterioration associated with biological aging and health problems. The final tier emerges from the organism's cognition about its own cognitive ability. Characterized by metacognitive abilities, this tier results from the interaction between the biological substrate and individuals' interaction with the environment. Like tier two, this tier emerges late in life, and is relatively resistant to changes in biological functions and health status. In sum, we might expect changes in health status to affect performance on fluid abilities, but not on more crystallized cognitive or metacognitive measures.

The belief that impaired health impinges on cognitive functioning has been borne out in the literature (see Elias et al., 1990; Siegler & Costa, 1985 for reviews). The following review is organized into three sections. First, the influence of objectively measured health characteristics on cognitive performance will be examined. Next, the focus will change to studies that have utilized self-report indices of physical health. Finally, some limitations of previous work will be examined, and the benefits of the current study will be outlined.

Objectively Measured Physical Health and Cognition

The study of the health status/cognition relationship can be characterized as proceeding on two parallel courses, each depending on how health status has been operationalized. One source of evidence comes from studies that employ medical, objective evaluations of health status. In these studies, health status is defined by the presence or absence of various disease manifestations. Hypertension and cardiovascular diseases have received the greatest attention in the literature. This interest reflects the fact that these diseases are very common age-associated conditions that contribute to high levels of morbidity and mortality. For instance, cerebrovascular- and hypertension-related disorders were the second leading cause of death among British Columbians aged 45 to 64 years in 1990 (British Columbia Ministry of Health and Ministry Responsible for Seniors, 1994).

There is consistent evidence suggesting that various manifestations of cardiovascular disease are associated with impaired cognitive functioning. For instance, Barrett and Watkins (1986) report that indicators of cardiovascular disease were associated with older adults' poorer performance on a free recall task. Schaie's longitudinal study of adult intelligence (see Schaie, 1988, 1994, for reviews) also provides evidence for the influence of cardiovascular disease on adult intellectual performance. Hertzog et al. (1978) examined the relationship between cardiovascular disease and intellectual performance in a group of 156 individuals between 1956 and 1963. They found significant differences between people classified according to presence or absence of cardiovascular disease on a number of cognitive tests. Specifically, absence of cardiovascular disease was associated with better performance on the verbal meaning, reasoning, and numeric ability subtests of Thurstone's primary mental abilities, as well as composite indicators of IQ and Educational Aptitude. Further, the non-impaired group scored higher on the Motor-Cognitive rigidity factor scale from Schaie and Parham's (1975) Test of Behavioral Rigidity. Finally, a significant Cardiovascular Disease X Time of Measurement interaction was observed for psychomotor speed, with cardiovascular subjects declining more rapidly than their noncardiovascular counterparts.

Although there is consistent evidence for the detrimental effects of acute cardiovascular disease on cognitive performance, the relationship with more benign forms of cardiovascular disease, such as hypertension, remains unclear. Speith (1965) noted that hypertensives who were not under medication performed poorly on psychomotor tests, such as complex reaction time, Trails A and B, and the digit-symbol substitution test. However, hypertensives who were taking prescribed medication performed at a level consistent with normal, healthy adults.

Similarly, Elias, Robbins, Schultz and Pierce (1990) reported that higher diastolic blood pressure was related to poorer performance on both psychomotor (tactile perception, Trails B) and reasoning (categories) subtests of the Haltstead-Reitan neuropsychological battery. Blood pressure scores were not related to performance on digit symbol substitution or finger tapping. Unlike Speith (1965), Elias, Robbins, Schulz, et al. (1990) found no differences between the results for individuals were currently medicated or unmedicated. Finally, Wilkie and Eisdorfer (1971) reported longitudinal declines in hypertensives full-scale and performance WAIS IQ scores over a 10-year period. Among the specific subtests that were affected by high blood pressure were: Digit span, digit symbol substitution, block design, and object assembly.

Although several studies have observed relationships between cognitive performance and hypertension, several have not. For instance, Hertzog et al. (1978)

observed a slightly different pattern of results when the classification of cardiovascular disease was changed from presence/absence to specific subtypes of the disease. They observed reliable decrements in the spatial ability, numeric ability, psychomotor speed subtests, as well as overall IQ, for three subtypes of cardiovascular disease (atherosclerosis; hypertension and atherosclerosis; cerebrovascular disease). However, individuals with uncomplicated hypertension declined only on psychomotor speed, and actually increased in spatial ability, numeric ability, and IQ performance. Other studies have noted that, when compared to normotensive individuals, the intellectual, motor and psychomotor decline associated with hypertension is either not observed (Costa & Shock, 1980) or is trivial (Elias, Schultz, Robbins, & Elias, 1989, Elias, Robbins, Schultz, Streeten, & Elias, 1987). In sum, although there is clear evidence that significant cardiovascular disease is related to poorer cognitive performance, the relationship to hypertension is affected by several factors. One important factor appears to be whether individuals are currently taking medication to control their hypertension.

Another line of research examining the role of physical health in predicting cognitive performance have utilized physiological measures of health status. Often, these studies are conducted in the context of examining the influence of physical exercise on cognitive performance. Although the literature on exercise and cognition is too extensive to review here (see Bashore & Goddard, 1994; Tomporoski & Ellis, 1986, for reviews) several studies may provide a glimpse of the relationship between cognition and physiological measures of health status. For example, Clarkson-Smith and Hartley (1989) examined the performance of high- and low-exercise individuals on a variety of cognitive tests. Individuals were classified according to the number of hours of strenuous physical exercise they participated in, as well as the number of calories expended during these physical activities. The groups were not significantly different in terms of heart rate or blood pressure, but the high-exercise group had a higher vital capacity (peak expiratory flow) than the low-exercise group did. Results indicated that high exercisers performed better than low exercisers on working memory and reaction time, with the strongest effects for reasoning. Although level of exercise was a significant predictor of cognitive performance, neither self-rated health nor number of medical conditions influenced performance on the cognitive tasks.

Dustman et al. (1984) also reported an association between exercise and increased cognitive performance. In their study, the effects of a four-month aerobic exercise conditioning program on neuropsychological test performance was examined. Dustman et al. found that the exercise intervention program improved digit symbol substitution, simple reaction time, and Stroop task performance, but not overall IQ. The increases in cognitive test performance were mirrored by increases in VO_2 max uptake.

In sum, when physical health is measured by physiological means, there is evidence that those individuals with superior physiological health perform better on cognitive tests than individuals who are in poorer health. This relationship is especially true when speed-related cognitive tests are used as outcome measures.

Self-Reported Physical Health and Cognitive Performance

Because of the relative expense of obtaining objective measures of health, both in terms of time and money, many studies have utilized self-report indices of physical health. It is the case that self-report measures of physical health are positively correlated with more objective indicators (Botwinick, West, & Storandt, 1978; LaRue, Bank, Jarvick, & Hetland, 1979; Maddox & Douglas, 1973). However, Elias et al. (1990) note that the correspondence between self-report measures of physical health and objective indicators of the presence of disease cannot be assumed to be veridical. The correlations between self-report measures and objective measures are modest, and some objective measures of disease are inversely related to self-reported health. In addition, self-report measures of physical health have been shown to be related to aspects of personality such as neuroticism (Costa & McCrae, 1985), as well as depressive symptomatology (Elias et al., 1982). Self-assessments of physical health may therefore reflect the ways in which various aspects of health, both subjective and objective, combine within the individual's perceptual framework (Tissue, 1974). Nevertheless, such assessments can be an important indicator of health status. For instance, Kaplan (1982, reported in Siegler & Costa, 1985) noted that individuals who rated their health as poor were 2.44 times more likely to die within a 7-year period than those who rated their health as excellent. Similar results were reported by Mossey and Shapiro (1982), who noted increased risk of premature death as a function of poor self-rated health. Thus it appears that a simple rating of overall health may be a proxy for some important predictors of survival.

Studies relating self-report measures of physical health to cognitive performance have reported mixed results. Several studies have found reliable relationships between cognitive performance and self-rated health status. For example, Perlmutter and Nyquist (1990) found that self-reported health measures, including overall self-ratings and the reported presence/absence of various chronic health conditions, predicted significant portions of variance in memory span and fluid intelligence in a group of 20- to 80-year-olds. Memory span was indexed by forward and backward digit span, while fluid intelligence was measured by the block design and digit symbol substitution subtests of the WAIS-R. Moreover, this result was independent of the effects of gender and education, which had been controlled statistically. Self-reported health did not predict significant portions of variance in crystallized intelligence, as measured by the WAIS-R vocabulary and information subtests. Similar results were reported by Hultsch et al. (1993). In this case, health status was indicated by a factor measuring self-reported presence of chronic illness, overall health self-ratings, number of illness episodes (visits to the doctor, days sick in bed), number of prescription medications, and the extent to which health problems interfered with daily activities. They found that health status predicted significant portions of variance, ranging from 1% to 3%, in processing speed, working memory and text recall. These effects were independent of age, education, gender, and neuroticism, which were controlled statistically. Health did not predict performance on tests of vocabulary, verbal fluency, fact recall, or word recall.

Field, Schaie, and Leino (1988) examined the relationship between health and performance and verbal IQ scores, measured by the WAIS, in a sample of 60- to 79-year-olds followed over a 14-year period. They measured self-reported health by summing four indicators of health status, including: An overall self-rating, how health affected their activities, rating of health compared to when they were 40, and a rating of the individual's energy by the experimenter. Cross-sectionally, health status predicted performance IQ, but only at the latter time of measurement. Verbal IQ was not related to health status at either time of measurement. Field et al. (1988) also examined the relationship between declines in IQ and health status. They found that neither declines in performance or verbal IQ were predicted by health status. However, it must be noted that the stability coefficients for performance and verbal IQ were quite high over the 14-year period (.83 and .86, respectively), thereby minimizing the potential for prediction of individual differences in IQ. However, Hertzog, Dixon and Hultsch (1992) found evidence suggesting a longitudinal relationship between changes in health status and cognitive performance. They assessed the text recall performance of a group of seven elderly women tested weekly for up to 2 years. In addition to the high level of intraindividual variability in text recall, two women exhibited significant declines in performance. These two women were characterized by deteriorating physical health.

Finally, Earles and Salthouse (1995) examined the relationship between health status and cognition using structural equation modeling. They found that a cardiovascular factor, indexed by whether participants reported that they had required cardiovascular surgery or were currently taking blood pressure medication, predicted performance in simple motor speed, but not perceptual speed or reaction time. Once the effects of the cardiovascular factor were modeled, no direct paths from a self-rated health factor, indexed by four ratings of overall health, were required. Taken together, Earles and Salthouse concluded that, "health status was associated with only a relatively small portion of the age-related variance in speed" (p. 40).

Although several studies have found significant relationships between health status and cognitive performance, several other studies have failed to do so. Salthouse et al. (1990) examined the effects of controlling for self-reported health status on age differences in performance on several cognitive measures, including speed, memory span, associative memory, and inductive reasoning. Results indicated that the age trends on all cognitive measures remained virtually identical when the effect of self-reported health was controlled compared to when it was not controlled. Similarly, Arbuckle et al. (1986) found no effect of a 9-point self-rating of health on a composite memory indicator, including digit span, free recall, and recall of factual knowledge questions.

There are several sources of influence that may account for the conflicting results that are observed. In the next section, three of these factors will be reviewed. The review will focus primarily on the use of self-report measures of health status and this is done for two reasons. First, self-report measures are the most widely accessible form of health status indicators, and do not consume a great deal of time or money in their administration. Second, the majority of the health measures used in the current study are self-reports, therefore a description of the problems inherent in the measures seems warranted. However, it should be noted that many of the factors that complicate the study of self-reported health and cognition may also apply to studies that use more objective indices. The three factors that may account for the conflicting results are: (a) Factors related to the sample composition, (b) how health is operationally defined, and (c) what types of cognitive outcome variables are used. After each factor is addressed, the potential benefits of the present study will be outlined.

Methodological Challenges in the Study of Health and Cognition

Factors related to sample composition include two components. First, how individuals are sampled into the study, and second, the types of subject characteristics that are measured. The first point relates to the issue of whether conflicting results are due to the fact that the level of disease typically observed in most older, community-dwelling, volunteer samples is sufficiently marginal to produce little variation in health status. For example, the majority (81%) of the sample used by Hultsch et al. (1993) rated their health as good or very good. Only two percent of the sample rated themselves as being in poor health. Similar results are reported by Salthouse et al. (1990), where the average rating of health was in the good to excellent range (see also Earles & Salthouse, 1995, Field et al., 1988; Perlmutter & Nyquist, 1990, for similar results). It may be the case that the relatively weak, or nonexistent, relationships that are observed between health status and cognitive performance are related to the limited variability of the health measures. Put simply, one would not expect strong relationships with health if nearly everyone rates themselves as being healthy. Samples with more diversity may exhibit stronger relationships to cognitive performance. In the current study, a population-representative sample was used. It was expected that such a diverse sample would increase the variability of the health conditions observed, and also increase the generalizability of the health/cognition relationship.

Another issue related to sample composition is the nature of the demographic and subject characteristics that are measured. Demographic characteristics, such as education, gender, age, and race, may influence the value individuals put on maintaining good health, reporting incidence of disease conditions, and/or the availability of health care. Age, in particular, is one characteristic that must be assessed when examining the health/cognition relationship. If age is not controlled, this could lead to an exaggerated relationship between health and cognition, because of the fact that incidence of disease is age-correlated. For instance, Perlmutter and Nyquist (1990) found that self-reported health accounted for 12% of the variance in memory performance and 20% of the variance in fluid intelligence. On the other hand, Hultsch et al. (1993) found that health status predicted, at most, 3% of the variance in working memory. One reason for these divergent results may be that Hultsch et al. (1993) statistically controlled for age, whereas Perlmutter and Nyquist (1990) did not use age as a covariate in their regression analyses. Therefore the discrepant findings may be related to the fact that the amount of variance that health status accounts for in Perlmutter and Nyquist's study is not only due to the influence of physical health, but also to the age of the participants.

An additional type of subject characteristic that can obscure the health/cognition relationship is related to individuals' personality characteristics. Elias et al. (1982) demonstrated that self-reports of health status are affected by level of depression. Similarly, Costa and McCrae (1985) have noted that individuals who score high on the neuroticism subscale of the NEO personality inventory also tend to report greater incidence of health impairment. Therefore, when using self-reports it is important to discriminate between those changes due to health conditions and those due to mental health factors. In the present study, an individual's personality characteristics are measured by a self-report of their current mental health, and by the Centers for Epidemiologic Study Depression scale. In the structural equation models that examine the health/cognition relationships, the influence of age, gender, education, race, and depression will be included into the predictive relationships. This allows the examination of the effect of health status on cognition without the influence of the potential confounds. Moreover, it allows for the examination of these subject characteristic variables on health status.

A second factor that may lead to inconsistencies in the relationship between health status and cognitive performance is how health is operationally defined. For example, the lack of relationship may be the result of health status being measured insufficiently. It is interesting to note that the two studies that failed to find a relationship between health status and cognition (Arbuckle et al., 1986; Salthouse et al., 1990) used single item self-ratings of health status. These rather crude assessments of health status may not adequately dimensionalize the concept. Other studies have treated health as a multi-dimensional concept and, in addition to overall ratings of physical health, have assessed presence of various chronic diseases, number of prescription medications, and the extent to which health status impairs functional ability.

In the current study, Liang's (1986) view that self-reported physical health is a multidimensional construct incorporating medical, social, and psychological aspects, was adopted. The medical component of physical health was assessed through reports of health problems or chronic illnesses and estimates of the number of days spent sick or disabled during a specific period of time. The social aspects of physical health were indexed by reports of the capacity to perform one's roles in relation to self-maintenance and instrumental activities of daily living. Finally, the psychological aspects of the construct were reflected in subjective ratings of one's overall physical health. From this perspective, several aspects of self-reported physical health must be tapped in order to adequately measure the individual's global perceptions of his or her health. In the present study health status was indexed by: objective measures of health (grip strength, vital capacity), and self-reports of overall health, chronic diseases, and illness episodes, and limits to daily activities. Using this variety of measures, we are able to adequately quantify individuals' health status, as well as determine whether particular groups of measures are more predictive of cognitive performance than others.

The third, and final, factor that may account for inconsistencies in the health/cognition relationship concerns the type of cognitive variables that are measured. In studies that have examined multiple indicators of cognitive performance, it is often the case that more "fluid" or speed-related measures are predicted by health status, whereas "crystallized" or knowledge-based measures are not. For example, Hultsch et al. (1993) observed health status was predictive of performance on the fluid abilities of verbal speed and working memory, but not of the crystallized indicators of verbal comprehension, verbal fluency, and fact recall. However, health status was also predictive of text recall, which might be considered to be a more complex task. The latter result may be due to the fact that text recall has a large contribution from working memory (Kintsch, 1974, Hultsch, Hertzog, & Dixon, 1990). In general, it is the case that health status predicts performance on fluid and psychomotor tasks, but is unrelated to more crystallized abilities (Field et al., 1988; Perlmutter, 1988; Perlmutter & Nyquist, 1990). In the current study, the performance on two types of cognitive tasks, word recall and reasoning was examined. This allows conclusions to be made regarding whether there is a differential relationship between health status and abstract reasoning, or word recall.

Summary/Conclusions

In sum, there is partial evidence for a relationship between individual differences in health status being predictive of differences in cognitive performance. This relationship is especially true when fluid indicators of cognitive performance are used as outcome measures. However, there are a number of factors that complicate the study of health and cognition and may account for inconsistencies in results that are sometimes observed. Three factors that may account for the conflicting results are: (a) factors related to the sample composition, (b) how health is operationally defined, and (c) the types of cognitive outcome measures that are used.

In the current study, the relationship between physical health and cognitive performance is examined in a large, population-representative sample of adults. Health is indexed by objective, physiological indices of health status, as well as self-reports of the medical, social, and psychological aspects of health status. Finally, measures of word recall and abstract reasoning are used as the cognitive outcome measures.

Environmental Complexity and Cognitive Performance

In addition to physical health, psychologists have evinced increasing interest in the role that environmental factors play in influencing intellectual performance. The focus of the present study is influenced by Schooler's environmental complexity hypothesis (1987, 1989, 1990). According to this hypothesis, the complexity of an individual's environment is defined by its stimulus and demand characteristics. The more diverse the stimuli, the greater the number of decisions required, the greater the number of considerations to be taken into account in making these decisions, and the more ill-defined and apparently contradictory the contingencies, the more complex the environment. To the degree that patterns of reinforcement within such an environment reward cognitive effort, individuals should be motivated to develop their intellectual capacity and to generalize the resulting cognitive processes to other situations. In contrast, Schooler suggests that simple environments may not provide sufficient support for the maintenance and enhancement of cognitive functioning. Consequently, prolonged exposure to such environments may lead to declines in cognitive abilities, as well as changes in self-efficacy and other noncognitive characteristics of the individual.

The potential for characteristics of an individual's environment to influence cognitive performance may be best understood when framed within the "disuse" perspective of cognitive aging (Salthouse, 1991). Essentially, the disuse perspective attempts to account for age differences in cognitive performance in terms of changes in the nature of activities performed by people of all ages. It is hypothesized that age-related changes in the pattern and frequency of daily activities are responsible for many of the age differences observed in measures of cognitive functioning. For example, evidence for the disuse perspective comes from studies that have manipulated experience by means of training or practice. Schaie and Willis (1986; see Willis, 1989 for a review) administered training programs to individuals who exhibited longitudinal declines on reasoning or spatial abilities, as measured by the Primary Mental Abilities reasoning and space tests. Participants completed a battery of psychometric tests both before and after five 1-hour training sessions. The training sessions targeted only one of the abilities, such that half of the participants were trained on reasoning ability and the other half were trained on spatial ability. Schaie and Willis found that ability specific training effects were present, in that improvement on reasoning ability was shown for individuals who were trained on these tasks, with similar results occurring for the spatial training group. In this case, providing experience, in the form of training, acts to improve reasoning and spatial ability.

Additional evidence comes from studies that have compared individuals who differ in terms of relevant experience. Differences in experience may be related to the individual's status as a student, his or her occupation, or aspects of an individuals lifestyle. Because much of the literature relevant to this topic will be reviewed below, only the rationale for this line of inquiry will be addressed here. Essentially, the argument is that the stimulation provided by cognitively demanding leisure activities or mentally demanding work environments may influence individual cognitive performance in a manner that is somewhat analogous to cognitive training. Specifically, individuals who work in these "enriched" environments have more experience with complex cognitive tasks, and this experience influences their overall cognitive performance level. In contrast, individuals who work in an occupational setting that emphasizes manual, rather than cognitive, abilities may not receive sufficient cognitive stimulation, which could result in poorer cognitive performance. As we will see from a review of the literature, there is some evidence to suggest that a relationship between the demands of leisure activities and work environments on cognitive performance does exist.

The present research was guided by the environmental complexity hypothesis as it applies to characteristics of individual's occupations. For example, do occupations that can be considered to be environmentally complex produce individuals who perform better on tests of cognition than people whose occupational environments are less complex? Similarly, are there specific characteristics of an individual's occupation (e.g., physical or mental demands) that are important determinants of cognitive functioning?

The following review is organized into three sections. First, evidence for the influence of environmental complexity will be provided in the form of studies that have examined participation in leisure activities. Next, studies that have examined the relationship between occupational complexity and cognitive performance will be reviewed. Finally, several limitations of previous research, and/or methodological challenges inherent in the study of environmental complexity and cognitive performance, will be outlined followed by how these limitations are addressed in the present study.

Leisure Activities and Cognitive Performance

Interest in the relationship between leisure-time activities and cognitive performance is motivated by the belief that participation in activities, particularly those that are cognitively demanding, may serve to maintain learning strategies and other mechanisms that would promote stability or enhancement of cognitive functioning. Thus, individual differences in the type and frequency of everyday activities engaged in by adults may be particularly important for cognitive functioning in later life.

Evidence bearing on this notion comes from several strands of research. For example, Craik et al. (1987) examined free recall ability of younger and older adults as a function of verbal ability and environmental engagement. They found that age-related differences were present in word recall for individuals with lower levels of verbal ability and relatively low levels of environmental engagement. In contrast, age differences were absent for those individuals with higher levels of verbal ability and high levels of participation in everyday activities. Similar results were reported by Hultsch et al. (1993). They examined the relationship between participation in complex, cognitively demanding activities and an array of information processing and intellectual ability measures. Hultsch et al. found that participation in cognitively demanding activities predicted significant portions of variance in measures of verbal speed, verbal fluency, word recall, and text recall. Moreover, Age X Activity interactions indicated that for verbal speed, vocabulary, and fact recall, this relationship became stronger with increasing age.

Further evidence comes from Arbuckle and her colleagues (Arbuckle et al., 1986; Arbuckle, Gold, Andres, Schwartzman, & Chaikelson, 1992; Arbuckle, Gold, Chaikelson, & Lapidus, 1994). Arbuckle et al. (1986) examined the relationship between a composite measure of memory performance and several contextual variables including education, level of participation in intellectual and social activities, and several aspects of personality in a large community dwelling sample of adults aged 65 to 93 years. They found that individuals with higher memory scores tended to be better educated, participated in more intellectual activities, and scored lower on measures of extraversion and neuroticism. Arbuckle et al. (1992) provide further evidence of the link between leisure activities and cognitive performance with a sample of World War II veterans tested twice over a 40-year period. They found that health, education, intellectual activity, and social support were related to better memory performance.

Additional longitudinal evidence is available from Schaie's Seattle Longitudinal Study. Schaie observed that one source of reducing the risk of cognitive decline in old age is the "substantial involvement in activities typically available in complex and intellectually stimulating environments" (1994, p. 310). Examples of these types of activities include reading, travel, attendance at cultural events, pursuit of continuing education activities, and participation in clubs and professional associations (Gribbin, Schaie, & Parham, 1980; Schaie, 1983). In sum, it appears that the active pursuit of complex leisure activities is related to superior cognitive performance. However, aspects of our leisure time do not constitute the only example of the complex environments in which we live. Indeed, one might argue that the one environment in which we spend most of our days, our work environment, may be sufficiently complex to influence our cognitive functioning. In the next section, the influence of work environment on cognitive performance will be examined.

Occupational Complexity and Cognitive Performance

Evidence for the relationship between occupational complexity and cognitive performance comes from several sources. Avolio and Waldman (1990) examined the relationship between job complexity and job type to indicators of general intelligence, numeric ability, and verbal ability as measured by the General Aptitude Test Battery (GATB). They found that both job complexity and job type predicted significant amounts of variance in general intelligence, numeric ability and verbal ability, independent of age and experience on the job. Specifically, job complexity predicted 9% to 13% of the variance in the three performance measures, whereas job type predicted 7% to 11% of the variance in these measures. Furthermore, an Age X Job type interaction indicated that age-related declines in cognitive performance were moderated by type of occupation. The Age X Complexity interaction was not significant.

More recently, Avolio and Waldman (1994) examined the relationship between GATB performance and type of occupation in a large sample (N = 24,219) of individuals. They found that job type predicted significant portions of variance, ranging from 1% to 4%, in general intelligence, verbal ability, numeric ability, spatial ability, clerical skills, motor coordination, and manual dexterity. In this case, the effect of occupational complexity was independent of age, race, gender, education, and occupational experience, which were controlled statistically.

Perhaps the most extensive investigation on the effects of occupational conditions on psychological performance has been conducted by Kohn and Schooler and their colleagues (Kohn & Schooler 1973, 1978; for reviews see Kohn & Schooler 1983; Kohn & Slomczynski, 1990). Kohn and Schooler (1973) examined 3,101 men employed in the United States in 1964. They focused on the relationship between the substantive complexity of an individual's occupation, defined as the extent to which a person could use initiative, thought, and independent judgment at work, and intellectual flexibility. Intellectual flexibility was indexed by five measures: An interviewer's appraisal of the subjects' intelligence, the propensity of the respondent to agree with agree/disagree questions, the embedded figures perceptual test, and two problem-solving tasks in which an interviewer rated the adequacy of the solution.

Results indicated that individuals who were given the opportunity to use judgment and initiative in work were more intellectually flexible than their colleagues in less self-directed occupations. This effect could not be ascribed entirely to the process of intellectually flexible individuals choosing self-directed occupations because the effect of substantive complexity on intellectual flexibility was larger than the reciprocal effect, which was statistically reliable however. Moreover, Kohn and Schooler controlled for several potentially confounding variables that might obscure the relationship, including age, education, race, national background, and religion of country in which the individual was raised.

The effect of substantive complexity on intellectual flexibility has also been examined longitudinally. Kohn and Schooler (1978) examined this issue by gathering a 10-year follow-up sample (N=687) representative of the original sample. Again, they found that substantively complex occupations affected individual's intellectual flexibility. Further, the magnitude of this effect was quite large, roughly one-quarter the size of the stability coefficient for intellectual flexibility itself.

Similarly, the effect of occupational self-direction on intellectual flexibility has also been replicated in several other populations attesting to the relative generalizability of the results. For example, Miller, Schooler, Kohn, and Miller (1979) found comparable effects of substantive complexity on intellectual flexibility for employed women. In this case, the sample consisted of the wives of the men who returned for their 10-year follow-up study. The analyses were patterned after the men's study. Results indicated that jobs that encourage occupational self-direction are related to effective intellectual functioning, as measured by intellectually flexibility. On the other hand, jobs that constrain opportunities for self-direction were related to poorer, or ineffective, intellectual functioning. The magnitudes of these relationships were similar to those obtained from men. Again, these relationships were independent of potentially confounding variables such as age, education, racial and religious background, as well as mother's and father's level of education and occupational status.

Several other studies conducted by Kohn, Schooler and colleagues attest to the cross-national similarities of the effect of occupational self-direction. Miller, Slomczynski, and Kohn (1985) examined the relationship between occupational self-direction and intellectual flexibility in a sample of Polish workers. They found similar relationships between occupational self-direction and intellectual flexibility in the Polish sample, as were found in the sample of American workers. Similarly, Naoi and Schooler (1985) found that the opportunity to use thought, initiative, and independent judgment, has real and significant effects on an individuals' intellectual flexibility in a sample of Japanese workers.

Recently, Small and Hultsch (1993) examined the relationship between occupational characteristics and cognitive performance. Using a subsample of the data used in the present study, participants rated their occupations on dimensions of physical demand, cognitive demand, stressfulness, and repetitiousness. Hierarchical regression analyses indicated that significant portions of variance in immediate recall, delayed recall, and reasoning could be predicted by individual differences in the four occupational characteristics. These effects were independent of the potentially confounding variables of age, eduction, gender, race, length of tenure, and health status.

Thus it appears that the complexity of our environments, both at work and at play, may exert an influence on our intellectual performance. However, like physical health, the relationship between environmental complexity and cognitive performance is complicated by a number of factors. In the following section, some of the limitations of the previous research, as well as some methodological challenges inherent in the study of this relationship will be outlined. After each factor is addressed, the potential benefits of the present study will be outlined.

Methodological Challenges in the Study of Occupational Complexity and Cognition

The following review will focus primarily on the difficulties of studying the relationship between occupational complexity and cognitive performance, and not on those problems associated with the study of leisure activities. Although this was done because the main focus of this study is on occupational complexity, many of the methodological difficulties associated with this relationship may also apply to the study of leisure activities. In general, the difficulties in studying the influence of occupational complexity on cognitive performance can be categorized into four types of factors: Demographic characteristics, cognitive outcome measures, measurement of occupational complexity, and length of occupational experience.

Various individual demographic characteristics may influence the relationship between occupational complexity and intellectual performance. For example, age, gender, and race may all influence the types of occupations that an individual is selected into. Perhaps the most influential demographic characteristic is years of education. Because occupational choice is limited by educational achievement, individuals with fewer years of education may be selected into jobs that emphasize physical or repetitious aspects of employment, rather than occupations that place demands on cognitive abilities. Because education is also related to superior cognitive performance, failure to control for education attainment may result in an exaggerated relationship between occupational complexity and cognitive performance. For example, Avolio and Waldman (1990) found that between 7% and 11% of the variance in the general, verbal ability, and numeric ability scales of the GATB could be predicted by the type of occupation the individual was employed in. On the other hand, occupation type predicted, at most, 4% of the variance in GATB performance in their 1994 study (Avolio & Waldman, 1994). One reason for these divergent findings may be that in their 1994 study they controlled for years of education, whereas in the 1990 study they did not. Therefore, the discrepancy in amount of variance that occupation type accounts for may be due to the fact that the variance that was accounted for in the 1990 study reflected both the influence of occupational complexity and educational achievement. Any studies that examine the influence of occupational complexity must, at the very least, control for the educational achievement of the participants.

An additional demographic characteristic that could obscure the relationship is health status. To the extent the individual's physical health is impaired, or perceived to be impaired, the nature of the available occupations may be restricted. Consequently, the predictive relationship between occupational complexity and cognitive performance should be assessed only after controlling for health status. In the present study, the effects of age, gender, race, education, and health status were controlled statistically before examining the relationship between measures of occupational complexity and cognitive performance.

A second factor deals with the type of cognitive outcome measures that are utilized to assess the influence of occupational self-direction on cognitive performance. Among studies that have examined this relationship, two distinct types of cognitive measures have been used: Objective measures of cognitive performance and more subjective measures. For example, Avolio and Waldman (1990, 1994) relied on the GATB instrument to measure performance. This is a fairly well-known cognitive battery with known reliability and validity properties. Small & Hultsch (1993) utilized measures of word recall (immediate and delayed) as well as the WAIS-R Similarities subtest. On the other hand, the measures of intellectual flexibility used by Kohn and Schooler and colleagues were a mixture of objective indices and subjective interviewer ratings. Specifically, intellectual flexibility was indexed by seven measures: (a) Goodenough intelligence estimate from Draw-a-Person test; (b)

Witkin sophistication-of-body-concept from the Draw-a-Person test; (c) Embedded figures test; (d) interviewer's appraisal of respondent's intelligence; (e) frequency of agreement in responding to agree-disagree questions; (f) rating of the adequacy of the answer to "What are all of the arguments you can think of for and against allowing cigarette commercials on TV?"; and (g) rating of the adequacy of the answer to "Suppose you wanted to open a hamburger stand and there were two locations available. What questions would you consider in deciding which of the two locations offers a better business opportunity?" To the extent that objective and subjective measures of intellectual ability differ, this could lead to inconsistencies in the relationship between occupational complexity and cognitive performance. Further, measures, such as those employed by Kohn and Schooler, are more appropriate cognitive outcome measures to use when studying the influence of occupational characteristics on cognition. This is due to the belief that "intellectual flexibility" may more closely match the abilities that are engaged in a complex work environment, whereas standardized tests of word recall or verbal intelligence may share few similarities with occupational tasks.

A third factor that may lead to inconsistencies in the relationship between occupational complexity and cognitive performance is how occupational complexity is operationally defined. Several studies (Avolio & Waldman, 1990, 1994) have defined occupational complexity from ratings of job demands from the Dictionary of Occupation Titles (DOT, United States Department of Labor, 1977). The DOT contains ratings of the complexity of the occupation in terms of interaction with people, data, and things. Other studies have used self-reports of occupational complexity (Kohn & Schooler, 1973, 1978; Small & Hultsch, 1993). To the extent that self- and standardized-ratings do not correspond, this could lead to inconsistencies in the relationship between occupational complexity and cognitive performance. In the present study, both self-report and standardized ratings (DOT job complexity ratings) of occupational complexity were examined. This allows for a more accurate assessment of the complex nature of various occupations. Moreover, it allows us to compare the correspondence between the self- and standardized-ratings of occupational complexity.

The final factor that could obscure the relationship between occupational complexity and cognitive performance is the amount of experience the person has in their occupation. Murphy (1989) argues that most occupations are characterized by long maintenance stages in which, "major job tasks are well-learned and can be performed with minimal mental effort" (p. 190). In contrast, transitions occur when an employee is new to a job, or when major duties or responsibilities of a job change. To the extent that occupations involve long maintenance phases, these environments may not sufficiently complex to influence overall cognitive functioning. Several investigators (Avolio & Waldman, 1990, 1994; Small & Hultsch, 1993) have addressed this issue by statistically controlling for differences in occupational experience. Perhaps a better way to address this issue is to compare individuals with relatively little experience against those with more years in their current occupation. In the present study, both assessment methods will be employed. In the majority of the structural equation models examining the relationship between occupational complexity and cognitive performance, differences in experience will be controlled statistically. However, additional analyses will be performed in which only individuals with less than one year experience will be used. This will allow a comparison between individuals with little occupational experience with those with many more years of job-related experience.

Summary/Conclusions

In sum, there is consistent evidence that the complexity of an individual's environment, whether at work or play, is predictive of individual differences in cognitive performance. However, like health status, there are several factors that act to complicate the study of this relationship. These influences can be categorized into four types of factors: Measurement of occupational complexity, cognitive outcome measures, demographic characteristics, and length of occupational experience.

In the current study, the relationship between occupational complexity is examined in a large, population-representative sample. Occupational complexity is indexed by both self-ratings and standardized indices (Dictionary of Occupational Titles job complexity codes). Further, measures of word recall and abstract reasoning are used as the cognitive outcome measures. Moreover, the relationship between occupational complexity is assessed independently of potential confounding variables such as age, education, race, gender, and physical health, which were all controlled statistically. Finally, the influence of occupational experience is assessed by comparing groups of individuals with more or less occupational experience.

Chapter III

OVERVIEW AND HYPOTHESES

Overview

The present study examined the relationship between physical health, occupational complexity, and cognitive performance in a United States population-representative sample of 23- to 85-year-old adults. The data were collected as part of the Health and Retirement Survey (HRS) by the Institute for Social Research at the University of Michigan (Juster & Suzman, 1993). The HRS was designed to investigate issues related to retirement and aging. Multiple aspects of an individuals' economic and personal information were assessed. These included: demographic information, physical health and functioning, housing and mobility, family structure, current job, past job, work history, disability, retirement plans, cognitive functioning, net worth, income, insurance, and widowhood. In the present study, three groups of variables were of most interest: (a) physical health, including self-reports of overall health, illness episodes, chronic illness, the extent to which health problems limit activities of daily living, and more objective indices such as vital capacity and grip strength; (b) occupational complexity, including self- and standardized-ratings of the complexity of individual's work environment; and (c) cognitive performance, which is indexed by measures of word recall and abstract reasoning ability.

The main analyses centered on two themes: (a) the relationship between physical health and cognitive performance; and (b) the relationship between occupational complexity and cognitive performance. In all cases, the relationships between physical health, job complexity, and cognitive performance were examined with structural equation models. Further, these relationships were assessed independently of potentially confounding variables such as age, education, race, gender, depression, and occupational experience.

One of the main differences between our previous analyses (Small & Hultsch, 1993) and the current study is the use of structural equation modeling, rather than hierarchical regression, to examine the relationships between physical health, occupational complexity, and cognitive performance. As such, it is useful to provide a brief description of the rationale for structural equation modeling, as well as discussing the overall analytic strategy used in the present study.

Structural Equation Modeling

Structural equation modeling (SEM) merges the logic of confirmatory factor analysis, multiple regression, and path analysis within a single data analytic framework (Bentler, 1980). The typical SEM consists of two parts: The measurement model and the structural regression model. The measurement model is a confirmatory factor analysis in which the variables that are measured empirically (the observed variables) are specified to be a linear combination of unobserved or latent variables (factors). The structural regression model is that part that specifies the regression relationships among the latent variables (Bentler, 1980).

There are a number of advantages in using SEM (see Alwin, 1988; Hertzog, 1987, 1990, for reviews). Perhaps the main virtue of SEM is the use of unobserved (latent) variables to construct relationships among concepts. The use of latent variables corrects the estimated relationships among variables by adjusting for unreliability in the observed variables. This is accomplished by modeling the observed variable as a function of the latent variable (variance it shares with other observed variables) and component-specific variance. This component-specific variance is residual variance (representing both unique and error variance) (Alwin, 1988). Because of this separation, relationships among latent variables are disattenuated for measurement error. Hertzog (1987) argued that "In cases where the communalities (variance in observed variables predicted by latent variables) are only moderate, the disattenuated correlations among factors can be considerably higher than the correlations among any pair of observed variables" (p.267).

A second virtue is that the use of SEM allows us to test specific hypotheses regarding the nature of the relationships among variables. In this way, we are able to compare how well the proposed model fits the data (see below for a discussion of model fit indices) before and after relationships among variables are constrained to zero, or allowed to be freely estimated. For example, Earles and Salthouse (1995) contend that the influence of self-rated health on cognitive performance is mediated through a cardiovascular illness factor, and paths from self-ratings of health to cognitive performance are not necessary. In the present context, this hypothesis can be tested by comparing the fit of the models that include, and exclude, paths from self-rated health to reasoning.

Although there are many virtues to using SEM, Breckler (1990) states there are also several "causes for concern" with the application of SEMs. Breckler classifies concerns according to issues related to: Equivalent models, model modification, and causal inferences. The issue of equivalent models is that if a model is found to provide a good global fit, it is very likely that other models will also provide a good (if not better) fit to the data (Breckler, 1990). In the present study, the potential for multiple good-fitting models is acknowledged, but attempts are made to eliminate additional models on theoretical or logical grounds.

The second issue, model modification, concerns the iterative procedure of producing a well-fitting model. When the model modification procedure is done using a single data set, the resultant model may be of questionable validity. The final model may be specific to only that particular data set, and its generalizability may be severely limited. Cudeck and Browne (1983) recommend model cross-validation with different samples in order minimize on the captilization of chance. In the present context, one sub-sample was used to derive a good-fitting model, while another sub-sample was used to confirm that the parameters derived from the first are replicable.

The final issue deals with drawing causal inferences from the data. Structural equation modeling goes by many names, one of which is causal modeling. Hertzog (1990) stated that "The term 'causal modeling' may eventually come to be understood as one of the most unfortunate labels ever created in social science research" (p. 262). This label might lead some to believe that cause and effect relationships could be derived from these analyses, even when correlational data is used. In the current study, the term "causal modeling" is avoided, and the models that are fit by the data are considered only in terms of their predictive relationship and are not interpreted causally.

Analytically, Bollen and Long (1993) state that five steps characterize most applications of SEMs: (a) Model specification, (b) identification, (c) estimation, (d) testing fit, and (e) respecification. In the next section, each step will be outlined followed by a discussion of the implications for the present study. The model specification and identification phases refer to the initial model that is formulated prior to estimation. This initial model is formulated on the basis of one's theory or past research in the area. For example, the structural relations model for self-reported physical health is based on Liang's (1986) health model, as well as predictions from the cognitive aging literature (e.g., Perlmutter & Nyquist, 1990; Hultsch et al., 1993) on the propensity for physical health measures to predict fluid abilities (e.g., reasoning) rather than more complex tasks (e.g., word recall). Further, the occupational complexity model was derived, in part, based on previous factor analyses (Small & Hultsch, 1993) on the job complexity measures.

The estimation phase concerns the selection of the statistical estimation technique that is used. This is often determined by the distributional properties of variables being analyzed (Bollen & Long, 1993). In the current study, the maximum likelihood (ML) technique is used to estimate the models. The ML technique assumes multivariate normality. Although this assumption is often violated, as it is in the present study, the ML procedure has been show to be robust to departures from normality, especially in large sample sizes, like those in the present study (Hu, Bentler, & Kano, 1992).

Once the model has been estimated, the fit to the data must be addressed. The standard practice in evaluating models involves attending to multiple goodness-of-fit indices. The χ^2 test is almost always significant, indicating less than perfect fit to the data, even when the model does a good job of reproducing the sample covariance matrix. This problem with χ^2 is especially pronounced when the sample size is large, as it is in the present case (Bollen & Long, 1993). Two alternative fit indices will also be reported: The Bentler-Bonett normed fit index (NFI) (Bentler & Bonnet, 1980), and the comparative fit index (CFI) (Bentler, 1990; McDonald, 1989). The NFI is an index of the proportion of the information in the sample covariances accounted for by the model. The CFI is a corrected estimation of the population value of NFI in which the index is adjusted for the χ^2 noncentrality parameter. Although the CFI is strongly advocated by some over the NFI (e.g., McDonald, 1989), it is often substantially higher than the NFI. As a result, both indices will be reported. Generally, fit indices above .90 are considered to be relatively good.

An additional method of assessing model fit is by sequential χ^2 tests. Sequential χ^2 tests are used to test nested models. A nested model is one in which the free parameters of one model are a subset of the free parameters in a second model (Bollen, 1989). For example, two models could be compared in which, in the first model all parameters are estimated freely, whereas in the second model several parameters are constrained to some value. In this case the change in model fit can be evaluated in order to determine whether the constraints in the second model produced a significant change in fit. This change in fit is evaluated by the formula:

$$\Delta\chi^2\ (df_2 - df_1) = \chi_2^{\ 2} - \chi_1^{\ 2}$$

The resulting $\Delta\chi^2$ is then compared with the χ^2 critical values, and the change in fit is deemed statistically significant or not.

The last step invariably involves model respecification. In this case, changes are made to the model and steps b-e are repeated, often multiple times. These changes are made in response to a poor fitting model and/or suggested changes by the modification indices. Modification indices provide information regarding the addition of parameters in order to improve the fit of the model. Although it is often the case that dozens of modification parameters are produced, the implementation of each parameter must be viewed in relation to its' theoretical plausibility. To the extent that model respecification becomes an iterative process this may lead to interpretative difficulties if the same data are used to refine and confirm the produced models. However, in the present study the sample was be divided into sub-samples that were used to refine and confirm the models.

Hypotheses

In this section, a series of five models will be outlined that correspond to the main hypotheses of interest in the present study. The first three models represent the relationship between various aspects of physical health and cognitive performance. The final two models deal with occupational complexity. Essentially, models were constructed based on prior research and theoretical expectations. The models that are outlined were fit to the data, and the adequacy of the fit was assessed.

The first set of models deal with the self-rated health characteristics. Based on Liang's (1986) health model, the self-rated health characteristics were expected to form four well-defined factors: Subjective ratings of health status, incidence of chronic illness, incidence of illness episodes, and difficulties with activities of daily living (ADL). Further, drawing on Liang's work, the interrelationships among these latent variables were expected to follow the pattern outlined in Figure 1. The medical aspects of health (chronic illness, illness episodes) were expected to predict the social (ADL) and psychological (subjective health) aspects of health status. Moreover, chronic illness should predict the number of illness episodes a person reports, and ADL should influence overall self-ratings of health status (subjective health). Among the cognitive variables, the relationship with health status is less clear. It was expected that health status will predict reasoning, but not word recall. This is based on the argument that health is more predictive of more fluid abilities, but not of more complex abilities (Hultsch et al., 1993; Perlmutter, 1988; Perlmutter & Nyquist, 1990). In the present model, the influence of physical health is modeled as mediated through self-ratings of physical health.

The next set of health structural models included a factor representing cardiovascular illness. The separation of cardiovascular illness from overall chronic impairment was based on the argument that CVD may be related to impaired cognitive performance (Earles & Salthouse, 1995; Elias et al., 1990). The factor

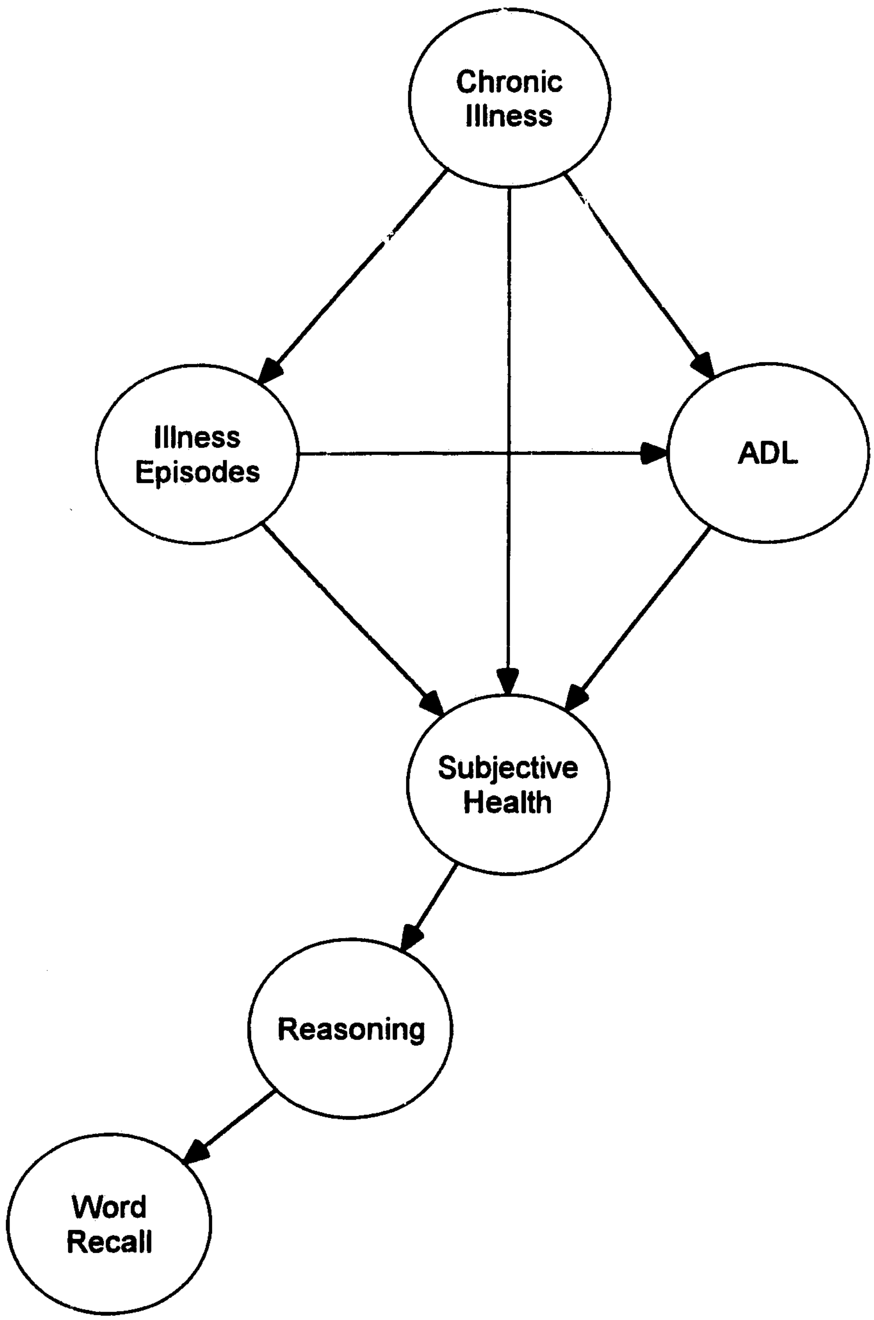

Figure 1
Self-Rated Health and Cognitive Structural Model
(independent of age, gender, race, education, and mental health, not shown)

structure is similar to that presented in Figure 1, except two factors will take the place of the one chronic illness factor. These two factors are: Cardiovascular disease (CVD), and chronic illness without CVD. The relationships to cognitive performance remained the same with the exception of the added paths from the cardiovascular disease factor to reasoning. The hypothesis that all of the health/cognition relationship can be mediated through cardiovascular illness (Earles & Salthouse, 1995) was also be tested by eliminating the path from subjective health to reasoning, and reexamining the fit of the model.

The final set of health structural models included the objective indicators of health status (grip strength, lung capacity). These physiological measures of physical health were included in order to ascertain whether self-reports of physical health were sufficient to predict cognitive performance, or whether more objective indices were needed to predict differences in cognitive ability resulting from differences in health status. Because these factors also represent medical aspects of health status they were modeled in a similar fashion to chronic illness. The relationship of the objective indices of health status to cognition was based on the results of Clarkson-Smith and Hartley (1989). They found that all of the relationship to cognition was predicted by vital capacity, while self-rated health and number of medical conditions were not predictive of cognitive performance. As such, all paths from the self-rated measures were eliminated, in favor of paths from grip strength and vital capacity to reasoning.

The final two sets of models deal with the relationship between various measures of occupational complexity and cognitive performance. In the first of the occupational complexity models, represented in Figure 2, the relationship between the self-rated occupational characteristics and cognitive performance was modeled. As seen in Figure 2, the self-rated characteristics were expected to form four factors based on an occupation's physical demands, mental demands, the extent to which the job requires people to analyze data or information (Data), and the extent to which an occupation allows individuals to decide how work is done (Freedom). The factor structure was based on a previous principal component analysis of the items (Small & Hultsch, 1993), as well as the item's face validity. Based on previous results (Small & Hultsch, 1993), it was expected that the strongest relationships will be between mental demand and reasoning. A second model was analyzed that included only individuals who have been employed in their occupations for less than one year. This examined whether occupational experience influences the relationship between occupational complexity and cognitive performance. It was expected that individuals with less than one year experience would exhibit stronger relations between job complexity and cognitive performance because they are still in a transition phase (Murphy, 1989), in which the environment is sufficiently complex to influence cognitive abilities.

The next set of models used the Dictionary of Occupational Titles (DOT, United States Department of Labor, 1977) standardized ratings of occupational complexity (see Figure 3). The DOT indicators assess the complexity of an occupation in terms of dealing with Data, Things and People (see Appendix B for a complete description of the DOT complexity codes). It was expected that the DOT

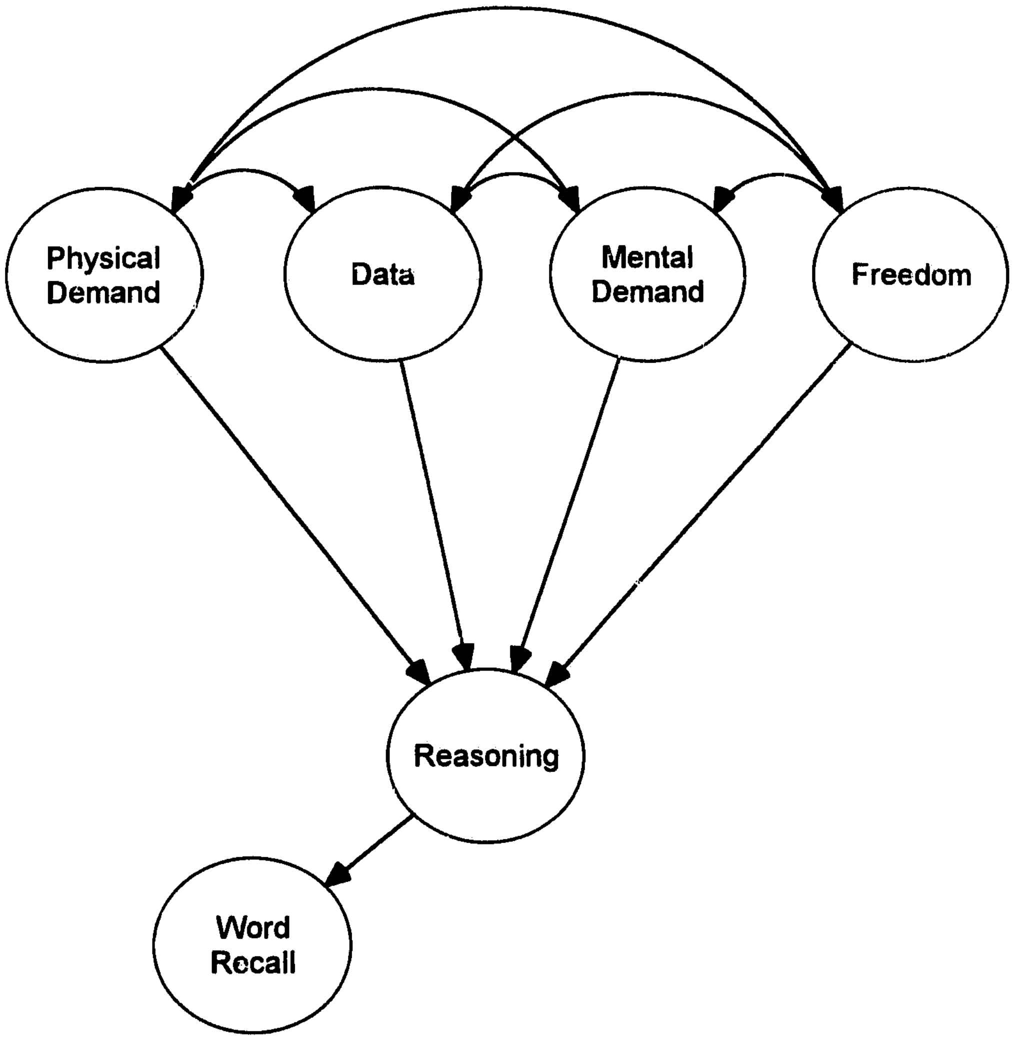

Figure 2
Self-rated Occupational Complexity, and Cognitive Structural Model (independent of age, gender, race, education, occupational experience and physical health, not shown)

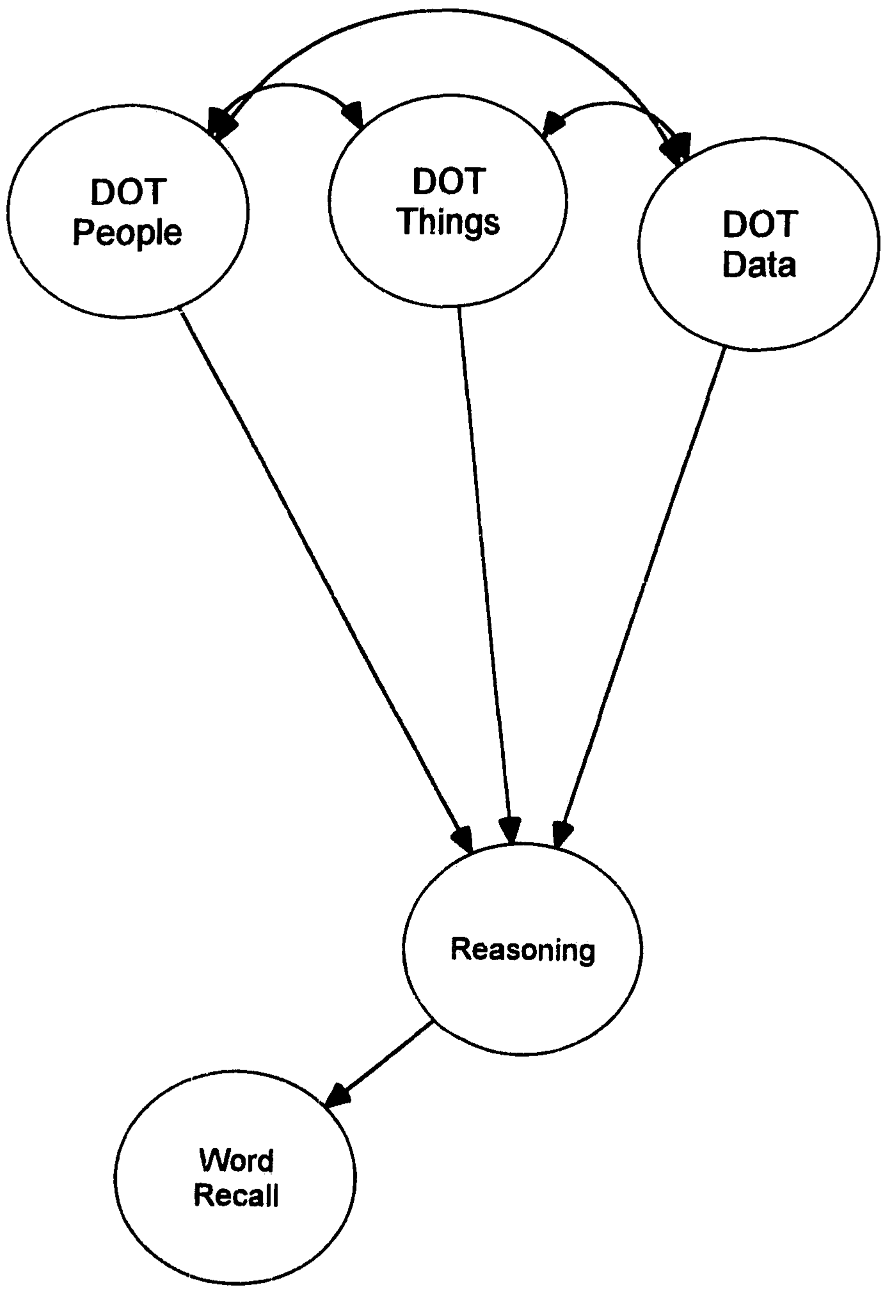

Figure 3
DOT Occupation Complexity, and Cognitive Structural Model (independent of age, gender, race, education, experience and physical health, not shown)

indicators would exhibit a similar predictive relationship to cognitive performance as the self-report measures. Two models were run, one that included people who are currently employed, and one that examined people who are unemployed. The contrast between the two models provided evidence as to whether the relationship between occupational complexity and cognition is a legitimate one, or simply represents a spurious relationship based on educational achievement or other unmeasured characteristics. It was expected that in the employed sample, the DOT complexity factors will predict cognitive performance, but they would not predict cognitive ability in the sample of unemployed individuals.

Chapter IV

METHOD

Participants

The sample consisted of 12,622 adults (5,852 men and 6,770 women) who were currently living in the United States between 1992 and 1993. The current sample was from the Health and Retirement Survey conducted by the Institute for Social Research at the University of Michigan. This survey is a population-based study investigating health and retirement issues in the United States.

The sample ranged in age from 23 to 85 (M= 55.6) years. The largest concentration of individuals occurred in the age range of 51 to 61 years. This was due to the fact that the HRS was designed to examine individuals transition to retirement, and people 51 to 61 years of age were most likely to retire. Breakdown of the sample by age revealed 1,590 (12.6%) individuals aged 27 to 50 years, 9,723 (77.0%) individuals aged 51 to 61 years, and 1,309 (10.4%) individuals aged 62 to 85 years. A further breakdown of the sample into decade of birth is shown in Table 1. A multivariate analysis of variance (MANOVA) performed on years of education and self-rated health characteristics of the sample by decade of age, revealed a significant effect of age group (Wilks' λ= .988, F (8, 25070)= 19.56, p < .001). As shown in the table, the older age groups had fewer years of education (F(4, 12536)= 19.00, p<.001), and reported poorer overall self-rated health (F(4, 12536)= 30.22, p<.001). Racially, the sample consisted of 9,111 (72.2%) Caucasian Americans, 2,064 (16.4%) African Americans, 1,172 (9.3%) Hispanic Americans, 154 (1.2%)

Table 1

Demographic Characteristics of the Sample by Decade of Age

Variable		Age Decade 20-39	40-49	50-59	60-69	70-89
N		139	1084	8391	2752	149
Age	M	35.71	46.26	54.69	62.00	73.00
	SD	3.43	2.47	2.68	2.29	3.11
Gender[a]	M	1.90	1.89	1.54	1.38	1.08
	SD	.30	.31	.50	.49	.27
Race[b]	M	1.29	1.27	1.29	1.25	1.37
	SD	.46	.45	.45	.43	.48
Years of	M	12.52	12.47	11.81	11.81	10.71
Education	SD	2.64	3.05	3.05	3.34	4.07
Self-rated	M	2.14	2.32	2.57	2.73	2.99
Health[c]	SD	1.05	1.16	1.20	1.21	1.23

[a] Gender: 1= Male, 2= Female
[b] Race: 1= Caucasian, 2= Non-Caucasian
[c] Self-reported health on a 5-point scale (1= excellent to 5 = poor).

Asian Americans, and 115 (.9%) Native Americans. For analytic purposes, race was dummy coded to indicate caucasian or non-caucasian (African-, Hispanic-, Asian-, or Native-American).

The educational and self-rated health characteristics of the participants are summarized in Table 2. A MANOVA performed on the demographic, self-rated health, and depressive characteristics revealed an overall effect for gender (Wilks' λ= .906, F (5, 10094)= 208.51, $p < .001$). Women were younger (F(1, 10098)= 917.30, $p < .001$), and had fewer years of education (F(1, 10098)= 7.88, $p < .01$) when compared to men. Further, women reported more depression-like symptoms than men (F(1, 10098)= 114.15, $p < .001$). There were no gender differences in overall self-rated health.

Cognitive Measures

Three indicators of cognitive performance were measured.

Episodic Memory. This domain was indexed by immediate and delayed word recall tasks. Subjects listened to a list of 20 common nouns presented at a rate of 1 word every 2 seconds (see Appendix A for a list of the words). Subjects were asked to recall the words, in any order, immediately after the entire list had been read to them, and again after a delay (M= 5.22 minutes). The delay was occupied by the reasoning test (described below) and ten questions rating the likelihood that certain economic conditions (e.g., inflation, depression) would occur in the future. Scores for the word recall tasks were the number of correct words recalled out of a maximum of 20.

Table 2

Demographic and Health Characteristics of the Sample

		Males N= 4474	Females N= 5626
Age	M	57.25	53.97
	SD	5.34	5.45
Race[a]	M	1.25	1.27
	SD	.55	.53
Years of Education	M	12.44	12.26
	SD	3.29	2.85
Self-rated Health[b]	M	2.51	2.48
	SD	1.17	1.17
CES-D[c]	M	15.10	16.03
	SD	3.97	4.64

[a] Race: 1= Caucasian, 2= Non-Caucasian
[b]Self-rated health on a 5-point scale (1=poor to 5=excellent)
[c] Depressive symptomatology (11= none to 44= severe)

Reasoning. This domain was indexed by a shortened version of the Word Similarities subtest of the WAIS-R (Wechsler, 1981). Subjects were asked to describe how two objects were alike. For example, in what way are an orange and a banana alike? Each of the six questions was evaluated on the quality of the answer given, based on criteria found in the WAIS-R manual (Wechsler, 1981). Specifically, no points were awarded for an incorrect answer, 1 point was awarded if a specific concrete likeness was given, and 2 points were given for an abstract generalization. Each subject received a total score out of a possible 12.

Health Measures

A variety of measures related to health status were collected using a combination of self-report, self-ratings, and objective measures of health status. The self-report measures were selected to tap four of the five components of self-reported physical health identified by Liang (1986): chronic illness, illness episodes, subjective health, and physical self-maintenance (Liang's fifth component, instrumental health, was not included). The items ranged from self-reports of specific diseases, health problems, and illness episodes, to self-ratings of overall health and the degree to which physical or health problems interfered with activities of daily living. The objective health measures were grip strength and vital capacity. In addition to the physical health measures, indicators of emotional health and depressive symptomatology were also administered.

Chronic Illness. This indicator was measured by reports of the presence of 14 chronic illnesses from eight broad categories [respiratory (e.g., bronchitis, asthma), circulatory (e.g., high blood pressure, high cholesterol, heart problems), nervous system (e.g., stroke, head injury), digestive/internal (e.g., kidney, stomach problems), infirmities (e.g., chronic pain, problems with feet and legs), glandular disorders (e.g., diabetes), arthritis/rheumatism, and cancer]. Subjects were asked to indicate whether they had experienced each of the 14 problems. The reports were summed to yield a single measure of chronic illness[1].

For several analyses, a separate cardiovascular illness factor was defined. Cardiovascular Illness was indexed by reports of the presence of high blood pressure, self-reports of whether individuals were currently taking antihypertensive medication, self-reports regarding whether individuals had seen a physician for heart problems within the past year, and whether they had ever experienced a heart attack or had heart surgery.

Illness Episodes. This measure asked subjects to report the number of illness episodes they had experienced during the past year. Five items reporting the number of nights confined to a hospital, number of visits to a physician, number of days sick in bed all or most of the day, number of overnight stays in a nursing home, and

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[1] Note that the use of a summed chronic illness score differs from Liang's (1986) original conception of the chronic illness factor as an induced variable (Alwin, 1988) of single indicators. The summed score was used for three reasons. First, it is advantageous because the use of a composite indicator reduces problems associated with variable nonnormality. Second, not all chronic conditions were expected to predict cognitive performance. Those that were expected to predict cognitive performance, namely cardiovascular illness, are separated from the overall chronic illness factor in subsequent analyses. Finally, Liang, Lawrence, Bennett, & Whitelaw (1990) evaluated the appropriateness of using composites in his health model and found that parameter estimates were closely approximated with composite variables.

number of nights requiring professional nursing care in the home were used. Subjects were asked to indicate the number of incidence in each category.

Self-Rated Health. This measure consisted of two items that asked subjects to rate their own health on a 5-point scale. Subjects were asked to rate their current physical health (1= excellent to 5= poor), and compare their current physical health to 1 year ago (1= much better to 5= much worse).

Physical Self-Maintenance. This measure asked subjects to rate how difficult various activities of daily living (ADL) were because of health or physical problems. Four dimensions of ADL's were identified (Liang, Borawski-Clark, Herzog, & Blaum, 1993). The four ADL categories (with indicator variables in parentheses) are: Personal ADL (bathing, eating, dressing), ambulation (walking across room, one block, several blocks), cardiovascular function (climb one, several flights of stairs, lift and carry 10 lbs), and fitness (sitting for long periods, lifting arms overhead, pushing and pulling). Subjects rated the difficulty of performing the activities on a 4-point scale (not difficult at all to very difficult/can't do). These reports were summed within categories to yield four ADL scores.

Grip Strength. Participants were asked to squeeze a hand dynamometer with their dominant hand. Participants made three separate attempts and the number of pounds squeezed was recorded. Participants who had surgery on their arm or hand in the past 3 months were excluded from participating. In order to standardize the measures, the grip strength measures that were used in the analyses were residualized for gender, weight, and height.

Vital Capacity. Participants were asked to expel air into a Mini-Wright Peak Flow meter. They were instructed to blow as hard and as fast as they could. Participants made three attempts on the vital capacity test. The peak flow, measured in Liters/minute, was recorded for each of the 3 trials. In order to standardize the measures, the vital capacity measures that were used in the analyses were residualized for gender, weight, and height.

Mental Health. Individual mental health was indexed by self-report and standardized measures. Participants were asked to rate their emotional health on a 5-point scale (1= excellent to 5= poor). Specifically, they were asked, "What about your emotional health - - how good do you feel or how stressed, anxious or depressed you feel?".

The second index of mental health was a shortened version of the Center for Epidemiologic Studies - Depressed Mood Scale (CES-D). The shortened CES-D is an 11-item scale designed to measure depressive symptomatology in the general population (Radloff, 1977). Participants were asked to indicate how each of eleven phrases "best describe how often you felt or behaved this way -- DURING THE PAST WEEK". The phrases included: I felt depressed, I felt that everything I did was an effort, my sleep was restless, I was happy, I felt lonely, I felt people were unfriendly, I enjoyed life, I felt sad, I felt that people disliked me, I could not "get going", and I did not feel like eating (my appetite was poor). Participants responded on a four-point scale from 1 (all or almost all of the time) to 4 (none or almost none of the time). The CES-D has been shown to have good reliability (Split-half and

Spearman-Brown reliability coefficients ranging from .77 to .92). The reliability of the shortened version of the CES-D in the current sample was very good (split-half reliability= .84). Moreover, it has excellent concurrent validity as evidenced by significant correlations with other depression and mood scales (Fischer & Corcoran, 1994). The appropriate items were rescored from their original reverse scoring, and the sum of the eleven items was used as the measure in the present analysis.

Occupational Characteristics

Subjects were asked to describe their current occupations on 12 dimensions ranging from how physically demanding their job was, to the types of intellectual demands that were placed upon them. Subjects rated how often the following items were true about their occupations: My job requires lots of physical effort, lifting heavy loads, stooping, kneeling, or crouching, requires me to use a computer, analyze data or information, do the same things over and over, the job affords a lot of freedom to decide how work is accomplished, requires me to learn new things. Subjects rated the accuracy of these statements on a 4-point scale (none or almost none of the time to all or almost all of the time). Subjects were also asked whether they agreed with the following statements, My job requires a very good memory, and my job requires me to do more difficult things than it used to. Again, subjects rated whether they agreed with these statements on a 4-point scale (strongly disagree to strongly agree).

Dictionary of Occupational Titles (DOT) Job Complexity Code.

The DOT is a compendium of 28,801 job titles. In addition to the title of the occupation, the DOT contains a three digit code indicating the complexity of each occupation in relation to data (i.e., information, knowledge, and concepts), people (i.e., interpersonal, communicating, monitoring, and negotiating), and things (i.e., machines, tools, equipment, and products) (see Appendix B for specific information on the DOT codes). Each of the listings is arranged from relatively simple tasks (high numbers) to complex tasks (low numbers). The DOT complexity data are based on extensive on-site observation of jobs as they are actually performed. In principle, an attempt was made to observe all occupations practiced in the United States, and assign them a complexity code. Cain and Treiman (1981) report reliability estimates for each of the DOT scales. The average reliability is .85 for the data code, .87 for the people code, and .46 for the complexity of dealing with things. The limited reliability of the 'things' subscale might be problematic for traditional attempts to study the occupational complexity/cognition relationship. However, because SEMs are used in the present study, this unreliability will be factored into the model, and perhaps a more accurate estimate of the relationship will be realized. A complete description of each DOT job complexity code can be found in Appendix B.

In the current sample, 87.5% of the occupations were successfully classified into one of the DOT job titles. The most frequent reasons for a job title not being classified were: (a) The occupation could have been classified into multiple job titles, with each job title having a different set of complexity codes, or (b) the job title listed in the data set did not correspond with any listed in the DOT.

<u>Procedures</u>

The questionnaires were administered individually, or with a spouse, in one session. The order of the questionnaires was: Demographic information, physical health and functioning, housing and mobility, family structure, current job, past job, work history, disability, retirement plans, cognition and expectations, net worth, income, insurance, and widowhood. In addition, one of ten "experimental modules" was administered to randomly selected groups of participants. These modules contained questionnaires or tasks that would have been too time consuming to administer to all participants, therefore random samples received each module. The physiological measures of vital capacity and grip strength were administered in one of these modules.

Length of interview ranged from 25 minutes to 315 minutes ($\underline{M}$= 96.10 minutes). The large range in interview length was due to the fact that in multiple-person households, only one respondent was asked to complete the entire questionnaire. In multiple respondent households, one member was selected as the primary respondent and answered the entire questionnaire, whereas the secondary respondent was only questioned about demographic, health, and cognitive abilities. Subjects were interviewed either face to face (N= 11,813) or over the telephone (N= 809).

Statistical Analyses

The confirmatory factor analyses and structural relations among the variables were estimated using the EQS structural equation modelling program (v. 4.02, Bentler, 1989). The structural equation models use covariance matrices as input. However, it is much easier to evaluate standardized solutions where factors and variables are rescaled to z-score form after the covariance structure model is estimated. In the standardized solution, factor loadings are expressed as standardized regressions of variables on factors, and relationships among factors are expressed as factor regressions. Where important, the original parameter estimates, expressed in covariance metric, will be reported.

Chapter V

RESULTS

This chapter is divided into five main sections. First, the interrelationships among the subjectively measured indicators of health status and cognitive performance are assessed. Second, a cardiovascular factor will be separated from the overall chronic illness factor, and the relationship between cardiovascular illness to cognitive performance will be examined. Third, the influence of both subjective and objective measures of health status on cognitive performance are addressed. The final two sections deal with measures of job complexity and their relationship to cognitive performance. In section four, the measures of job complexity were self-report indicators. In the last section, the DOT job complexity measures were utilized.

Physical Health and Cognitive Performance

Self-rated Health Measurement and Structural Models

Table 3 shows the means, standard deviations, and skewness for all of the variables to be used in the self-rated health models. From the table, it is easy to see that some of the variables are severely skewed. Most notably, those variables presumed to index activities of daily living and illness episodes are skewed. Bentler (1989) recommends skewness should not exceed $\pm$ 1.0. If skewed variables are used, the factor loadings, standard errors and chi-square statistics produced by the model may be incorrect. To address this problem, the activities of daily living and illness episode measures were dichotomized to indicate presence or absence of the health condition. While this is not an ideal solution because it eliminates variance

Table 3

Means, Standard Deviations, and Skewness of the Subjective Health Model Variables

(N= 10100)

Variable	Mean	Standard Deviation	Skewness
Age	55.42	5.64	-.28
Gender	1.56	.50	-.23
Race	1.26	.54	5.64
Years of education	12.34	3.06	-.78
CES-D	15.62	4.38	1.70
Mental health	2.48	1.06	.30
Immediate word recall	7.71	2.58	.56
Delayed word recall	5.82	2.62	.70
Reasoning	6.22	2.96	.01
Chronic illness including CVD	2.37	2.10	1.08
Chronic illness excluding CVD	1.58	1.55	1.09
Current health	2.50	1.17	.40
Retrospective health	2.92	.71	-.51
Nights in hospital	.97	5.78	15.22
Nights in nursing home	.04	3.07	96.19
Nights under nursing care	.45	9.99	30.91
Days sick in bed	4.01	23.77	11.79
Visits to doctor	4.37	8.45	6.25
Personal ADL	3.09	.55	7.79
Ambulation	3.58	1.46	3.12
Cardiovascular function	4.47	2.18	1.70
Fitness	4.03	1.69	2.05
High blood pressure	.38	.48	.51
Blood pressure medication	.24	.43	1.20
Heart attack	.05	.23	3.93
Doctor for heart	.08	.27	3.10
Heart surgery	.02	.15	6.31

that may be meaningful, Table 4 shows it dramatically reduces the problem of variable nonnormality. However, problems with nonnormality still persisted for the personal ADL measure, as well as variables indexing nights spent in hospital, in a nursing home, or under nursing care. An inspection of the distributions of these variables indicated floor effects existed for these four items. For instance, 96.0 % of the sample reported no difficulties with personal activities of daily living, 89.3% of the sample report spending no nights in the hospital, 99.9% of the sample report spending no nights in nursing home, and 99.1% of the sample reported that they spent no nights under nursing care. Because the overwhelming majority of the sample responded negatively to these items, these four measures were excluded from the measurement model.

In order to develop the structural equation models, the sample was randomly divided into four equal size sub-samples (N= 2525). The first two sub-samples were used to develop and replicate the self-rated health models using the composite chronic illness score. The last two sub-samples were set aside and used to construct the models partitioning chronic illness into its cardiovascular disease component. Table 5 presents the demographic and self-rated health characteristics of the first two sub-samples. A MANOVA comparing the demographic characteristics of the two samples revealed no significant differences (Wilks' λ= .999, $F(5, 5044)$= .503, p= .774), indicating the random selection created groups that were demographically comparable.

The first task was to develop a measurement model for the self-reported health and cognitive latent variables. A 7-factor model, based on Liang's (1986)

Table 4

Mean, Standard Deviations, and Skewness of the Subjective Health Model Variables

(N= 10100)

Variable	Mean	Standard Deviation	Skewness
Age	55.42	5.64	-.28
Gender	1.56	.50	-.23
Race	1.26	.54	5.64
Years of education	12.34	3.06	-.78
CES-D	15.62	4.38	1.70
Mental health	2.48	1.06	.30
Immediate word recall	7.71	2.58	.56
Delayed word recall	5.82	2.62	.70
Reasoning	6.22	2.96	.01
Chronic illness including CVD	2.37	2.10	1.08
Chronic illness excluding CVD	1.58	1.55	1.09
Current health	2.50	1.17	.40
Retrospective health	2.92	.71	-.51
Nights in Hospital[a]	.11	.31	2.55
Nights in Nursing Home[a]	.00	.02	41.00
Nights under Nursing Care[a]	.01	.09	10.51
Days sick in bed[a]	.31	.46	.81
Visits to Doctor[a]	.80	.40	-1.49
Personal ADL[a]	.04	.20	4.69
Ambulation[a]	.22	.42	1.34
Cardiovascular Function[a]	.52	.50	-.06
Fitness[a]	.42	.49	.31
High blood pressure[a]	.38	.48	.51
Blood pressure medication[a]	.24	.43	1.20
Heart attack[a]	.05	.23	3.93
Doctor for heart[a]	.08	.27	3.10
Heart surgery[a]	.02	.15	6.31

[a] Variable dichotomized to indicated presence/absence of the condition. Higher scores indicate greater impairment

Table 5

Demographic Characteristics of the Two Subsamples

used to Devise and Replicate the Self-rated Health Models

Variable		Sample 1 N= 2525	Sample 2 N= 2525
Age	M	55.44	55.25
	SD	5.50	5.77
Gender[a]	M	1.56	1.56
	SD	.50	.50
Race[b]	M	1.26	1.25
	SD	.53	.55
Years of	M	12.34	12.40
Education	SD	2.98	3.02
Self-reported	M	2.49	2.49
Health[c]	SD	1.17	1.16

[a] Gender: 1= Male, 2= Female
[b] Race: 1= Caucasian, 2= Non-Caucasian
[c] Self-reported health on a 5-point scale (1= excellent to 5 = poor).

conceptualization of health status, was hypothesized for the self-rated health and cognitive variables. The latent variables (with measured variables in parentheses) are: Chronic Illness (summed chronic disease measure), Illness Episodes (days sick in bed, number of visits to a doctor), ADL (ambulation, cardiovascular function, fitness), Subjective Health (current health, retrospective health), Reasoning (word similarities), Episodic Memory (immediate and delayed recall), and Mental Health (mental health, CES-D). Note that both single-and multiple-indicator latent variables were proposed in the measurement model. This was done to ensure that the Chronic Illness and Reasoning factors did not require additional loadings to, or from, the other factors. The single indicator latent variables were constructed in accordance to the recommendations of Hayduk (1987). She suggests constraining the error variance to some estimate based upon measure reliability. For example, the reliability of the word similarities test is estimated as .84 (Weschler, 1981)[2]. Therefore the unique variance in this variable is the product of 1-reliability (.16) and the variance of the indicator. For the chronic illness measure the unique variance was estimated as .1 times the variance of the measure. Sörbom and Jöreskog (1982) recommend constraining the variance of single indicators in this fashion when no other evidence of measure reliability is available. This procedure produces a somewhat conservative estimate of the unique variance of the measure.

2Note: This reliability is based on the full, 14-item word similarities measure. It may be the case that this estimate is not exactly the same for the shortened version used in the present context. Nevertheless, it is the best estimate of reliability that is currently available.

The initial measurement model for the seven factor model fit the data relatively well ($\chi^2(46) = 272.76$, $p < .001$, NFI= .969, CFI= .974). This measurement model, and the ones that follow, consisted of simple structure factors (Alwin, 1988). That is, only single loadings from measured variables to their respective factors were modeled. The standardized factor pattern weights (factor loadings) and the estimated communalities (variance in each measure accounted for by the factor) are reported in Table 6. An inspection of the table reveals that all measures had significant loadings on their respective factors. One problem did emerge; the loading of retrospective health on the Subjective Health factor. The standardized factor loading of this measure was only .254, accounting for approximately 6% of the variance in this measure. Two options were considered in dealing with this measure. The first was to simply leave the variable in the model and assume that the relatively low loading was due to the unreliability of this measure. The second solution was to reestimate the model with two single indicator latent variables representing Current and Retrospective Health. This was considered to be the best option because the low loading may not be due to unreliability, but rather the measure may be indexing another form of self-rated health. One index of self-rated health inquires about current health status, whereas the other indexes health from one year ago. Thus, the "retrospective" assessment may have real significance when estimating the effects of time-lagged health status on cognitive performance that may have been obscured in the factor including current health. Further, the perceived stability in health status can also be assessed in the model. The model including the

Table 6

Standardized Factor Loadings and Communalities for the Seven Factor Self-Rated Physical Health, Mental Health and Cognition Model

$\chi^2(46) = 272.76$, $\underline{p} < .001$, NFI= .969, CFI= .974

Variable	Chronic Illness	Word Recall	Reasoning	Subjective Health	Illness Episodes	ADL	Mental Health	Communality
Chronic illness	.949							.901
Immediate recall		.900						.810
Delayed recall		.877						.769
Similarities			.917					.841
current health				.795				.632
retrospective health				.254				.065
days in bed					.403			.162
doctor visits					.352			.124
ambulation						.654		.428
cardiovascular function						.620		.384
fitness						.536		.287
mental health							.772	.596
CES-D							.730	.533

single indicator Current and Retrospective Health latent variables fit the data well ($\chi^2(41) = 242.38$, $p < .001$, NFI= .972, CFI= .977). Table 7 shows the standardized factor weights and estimated communalities for this model. Again, all variables had significant loadings on their respective factors. No other changes seemed warranted from an inspection of residuals and other fit indices (Lagrangian multipliers).

The next step was to determine whether the measurement model defined in the first sample would be replicated in the second sample. This replication is crucial because replicating the measurement model on a different sample reinforces one's confidence of the generalizability of the factor structure (Breckler, 1990; Cudeck & Browne, 1983). The measurement model from the first group was used as the basic model for both samples. This solution fit the data relatively well ($\chi^2(82) = 363.51$, $p < .001$, NFI= .978, CFI= .983). Accordingly, this model was seen as a reasonable foundation for further tests of cross-sample equivalence of the model parameters. The constraints that the unstandardized factor pattern weights were equal across the samples was added. Adding these constraints on the two samples did not significantly change the fit of the model ($\chi^2(87) = 364.25$, $p < .001$, NFI= .978, CFI= .983; $\Delta\chi^2(5) = .74$, $p > .05$). Based on these results it was concluded that the measurement model devised in the first sample fit the second sample as well, and the results were not simply due to chance. This measurement model was therefore used as the basis for the structural relations models that follow.

Table 7

Standardized Factor Loadings and Communalities for the Eight Factor Self-Rated Physical Health, Mental Health and Cognition Model

$\chi^2(41) = 242.38$, $p < .001$, NFI= .972, CFI= .977

Variable	Chronic Illness	Word Recall	Reasoning	Current Health	Retrospective Health	Illness Episodes	ADL	Mental Health	Communality
Chronic illness	.949								.901
Immediate recall		.900							.810
Delayed recall		.877							.769
Similarities			.917						.841
current health				.948					.899
retrospective health					.951				.904
days in bed						.395			.156
doctor visits						.359			.129
ambulation							.656		.430
cardiovascular function							.619		.383
fitness							.535		.286
mental health								.772	.596
CES-D								.731	.533

Before turning to the structural relations models, it is useful to examine the pattern of disattenuated factor correlations. As seen in Table 8, several interesting patterns emerge. Among the health measures, there are several strong relationships, accounting for between 5% and 49% of variance, between chronic illness, current health, illness episodes, and ADL. The relationships with retrospective health are smaller in magnitude, approximately .3% to 4% of variance. Among the cognitive measures, word recall and reasoning correlate strongly with each other, accounting for approximately 17% of variance. It is also the case that the health factors appear to correlate more strongly with reasoning, than word recall.

Although the interrelationships in Table 8 suggest that self-reported physical health may moderate cognitive performance, especially reasoning, the exact relationship is difficult to determine using disattenuated factor correlations. This is because the relationships may be mediated by other factors. Variables such as education, age, gender, race, and depression will be related to physical health, as well as cognitive performance. In order to examine the relationship between self-reported physical health and cognitive performance controlling for these potential confounds, the self-reported physical health, mental health, cognitive, and confound variables were entered into a structural equation model.

The hypothesized structural relations model is shown in Figure 4. Essentially, this is the same model as presented in Figure 1, and described in the overview and hypotheses chapter. The one major difference is how subjectively rated health status is now conceptualized. In this case, subjective health is represented by two single-

Table 8

Disattenuated Self-rated Physical Health, Mental Health

and Cognitive Factor Intercorrelations

	Factor							
Factor	1	2	3	4	5	6	7	8
1. Word Recall		.405	-.110	-.238	-.028*	.102*	-.135	-.176
2. Reasoning	.415		-.110	-.286	-.033*	.205	-.190	-.277
3. Chronic illness	-.123	-.129		.641	.192	.592	.715	.549
4. Current health	-.233	-.317	.651		.201	.382	.665	.619
5. Retrospective health	-.067	-.054*	.174	.224		.090*	.223	.276
6. Illness episodes	.101*	.058*	.616	.431	.059*		.468	.367
7. ADL	-.107	-.168	.727	.658	.229	.473		.592
8. Mental health	-.186	-.272	.528	.632	.273	.373	.605	

All correlations are significant except where indicated * $p > .01$.
Note: Sample 1 values in lower triangle, Sample 2 in upper triangle.

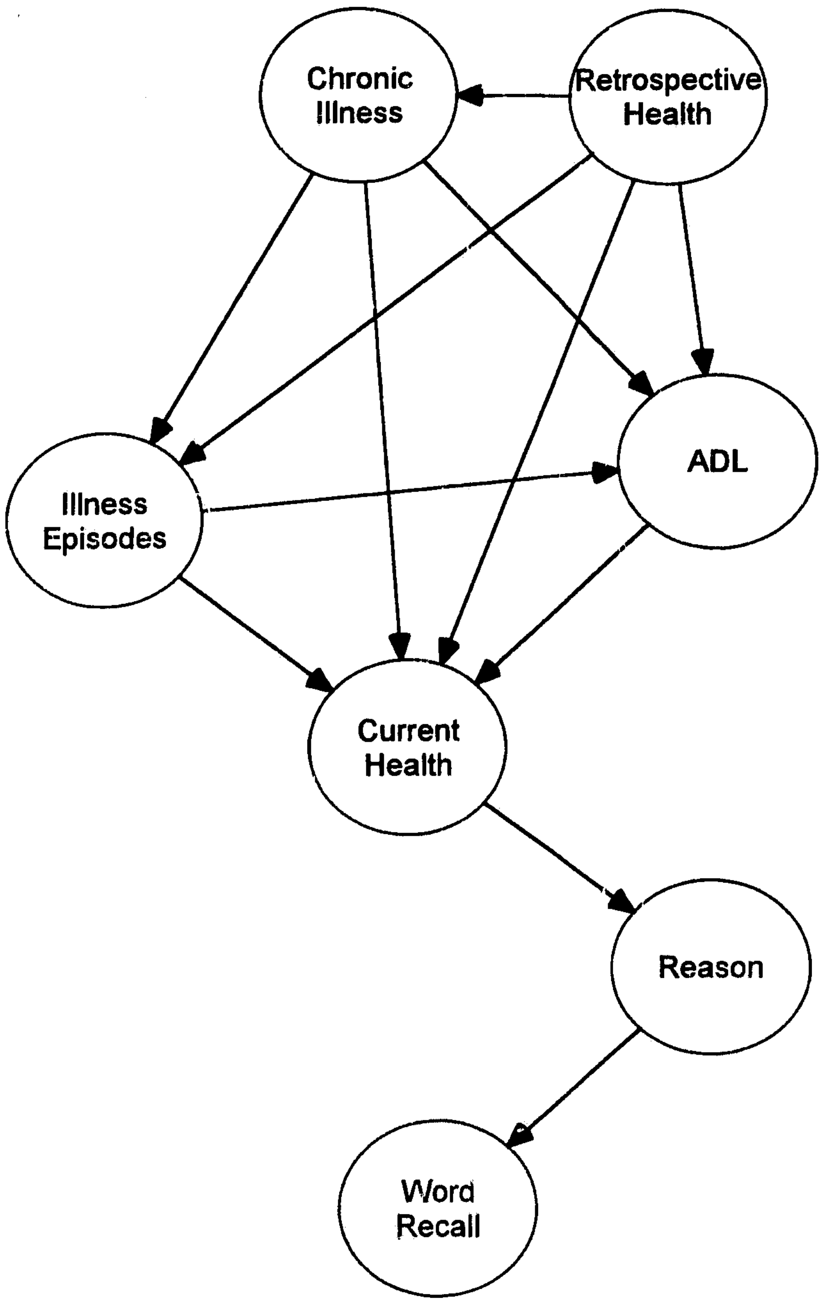

Figure 4

Revised Self-rated Health and Cognition Model
(Retrospective Health now included)

indicator factors, Current and Retrospective Health. In this model, the retrospective assessment of self-rated health is thought of as a predictor of chronic illness, illness episodes, ADL, and current health status. This was because retrospective health status may be a predictor of current impairment. All other paths were constructed in accordance with the predictions outlined in Figure 1. In addition to the aforementioned structural paths, each latent variable received paths from age, gender, race, years of education, and mental health (not shown in Figure 4). This was done to ensure that the relationships among the latent variables were not simply due to confounding demographic characteristics. The five demographic variables were allowed free to covary.

The initial structural model fit the data relatively well ($\chi^2(70)= 377.95$, $p < .001$, NFI= .965, CFI= .971). An inspection of the parameter estimates from the model revealed several of the paths were non-significant. In particular, the path from Retrospective Health to Illness Episodes was not statistically reliable ($z= -1.24$), nor was the path from Retrospective Health to Chronic Illness ($z= 1.17$). Similarly, the path from Illness Episodes to ADL was not statistically significant ($z= .06$). The non-significant paths were removed from the model and the analysis was rerun. The new model produced a good fit to the data ($\chi^2(73)= 380.79$, $p < .001$, NFI= .965, CFI= .971; $\Delta\chi^2(3)= 2.84$, $p > .05$). Note that the NFI and CFI goodness-of-fit indices are the same across the two models. This is an example of the "equivalent models" concern raised by Breckler (1990). In this case, the model that had the non-significant paths removed was chosen because it provided a more parsimonious fit to the data. An inspection of the modification indices revealed a path from Chronic Illness to Reasoning could be added to increase the fit of the model. Adding this path resulted in a significant increase in model fit ($\chi^2(72) = 374.79$, $p < .001$, NFI= .965, CFI= .972; $\Delta\chi^2(1) = 6.0$, $p < .05$). An inspection of the residuals and other fit indices suggested no other changes were warranted.

Before interpreting the final structural model, it is prudent to determine whether this same structure will replicate on the second sample. The final structural model fit both samples relatively well ($\chi^2(144) = 670.37$, $p < .001$, NFI= .968, CFI= .975). Constraining the measurement model parameters equal in both samples did not degrade the fit significantly ($\chi^2(149) = 673.72$, $p < .001$, NFI= .968, CFI= .975; $\Delta\chi^2(5) = 3.35$, $p > .05$). The next set of constraints required that all of the structural parameters in both samples be constrained equal. This analysis is critical to confirm that the parameter estimates derived in the first sample were not simply due to chance, but are able to be replicated. This model produced a slightly poorer, but not statistically worse, fit to the data ($\chi^2(194) = 706.06$, $p < .001$, NFI= .966, CFI= .975; $\Delta\chi^2(45) = 32.34$, $p > .05$). Although constraining all parameters equal did not significantly degrade the fit of the model, modification indices revealed releasing one of the constraints would improve the fit of the model. Specifically, allowing the path between age and Word Recall to be freely estimated in both samples would decrease the chi-square almost 5 units. The standardized path coefficient from age to Word Recall was -.154 in sample 1, and -.110 in sample 2. Since the constraint did not involve any of the relationships among the self-rated health or cognitive latent variables, and the difference in the parameter estimates was minor, the difference was considered to be a minor misspecification of the model.

The relationships among the demographic control variables and the health and cognitive variables are presented in Table 9. For the cognitive measures, both race and age are negatively related to performance, whereas gender and education are positively related to reasoning and word recall. Further, better self-reported mental health is related to increased word recall and reasoning performance. Among the health measures, in general, age is positively related to physical health, indicating an increase in medical conditions and poorer self-rated health with increased age. This is not true for illness episodes, however, whereby increased age is actually related to fewer illness episodes. Among the relationships between physical health and gender, women report more chronic illness, illness episodes, and problems with ADLs. However, women also rate themselves as being in better health than men. Race is negatively related to Chronic Illness, Retrospective Health, and ADL, indicating that non-caucasians rated health from one year ago as better, and reported fewer chronic illnesses and impairments of ADL. On the other hand, non-caucasians rated themselves as having poorer current health. Years of education is negatively related to current health, and ADL, indicating individuals with more years of education reported better current health and fewer impairments of ADLs. On the other hand, more years of ecuction was also associated with increased reporting of illness episodes. Finally, mental health was positively related to chronic illness, current health, retrospective health and ADL. This indicated that with increased problems

Table 9

Standardized Parameter Coefficients for the Demographic Control Variables and the Self-Reported Physical Health, and Cognitive Factors

	Factor						
Control Variable	Word Recall	Reasoning	Chronic Illness	Current Health	Retrospective Health	Illness Episodes	ADL
Age	-.154	-.071	.187	.054	.028*	-.104	.024*
Gender	.190	.044	.072	-.139	-.024*	.204	.144
Race	-.059	-.181	-.048	.081	-.055	.022*	-.015*
Education	.102	.456	.002*	-.187	-.005*	.256	-.056
Mental Health	-.097	-.081	.538	.256	.286	.106*	.271

All estimates are significant except where indicated * $p > .05$.

associated with mental health, there was an increased incidence of reports impairments of physical health.

The final self-reported health and cognition model, and parameter estimates, are presented in Figure 5. Focusing on the relationships among the health measures first, several interesting results emerge. First, retrospective health shows very little predictive power with current self-reports of physical health. Chronic illness, on the other hand, shows large, and statistically reliable relationships with all other health measures. The strongest relationships for Chronic Illness are with illness episodes, and ADL. Further, ADL and Illness episodes showed significant relationships to current health. In general, current self-rated health was well predicted by the model. Approximately 13% of the variance in self-rated health was predicted by the health measures, and an additional 13% of the variance was predicted by the demographic control variables. Note that this factor structure did not exactly replicated Liang's (1986) health model. The main difference between Liang's model, and the one estimated here is that in the current model, Illness Episodes does not predict impairments with ADL. Further, the standardized parameter estimates in the current model are somewhat smaller than those presented by Liang (1986). Several potential sources for these discrepancies are discussed later.

Among the cognitive measures, reasoning was predicted by the Current Health and Chronic Illness factors. Current health status predicts roughly 1% of the variance in reasoning. Paradoxically, more chronic illness actually predicts better performance on the word similarities measure. For word recall, none of the health measures

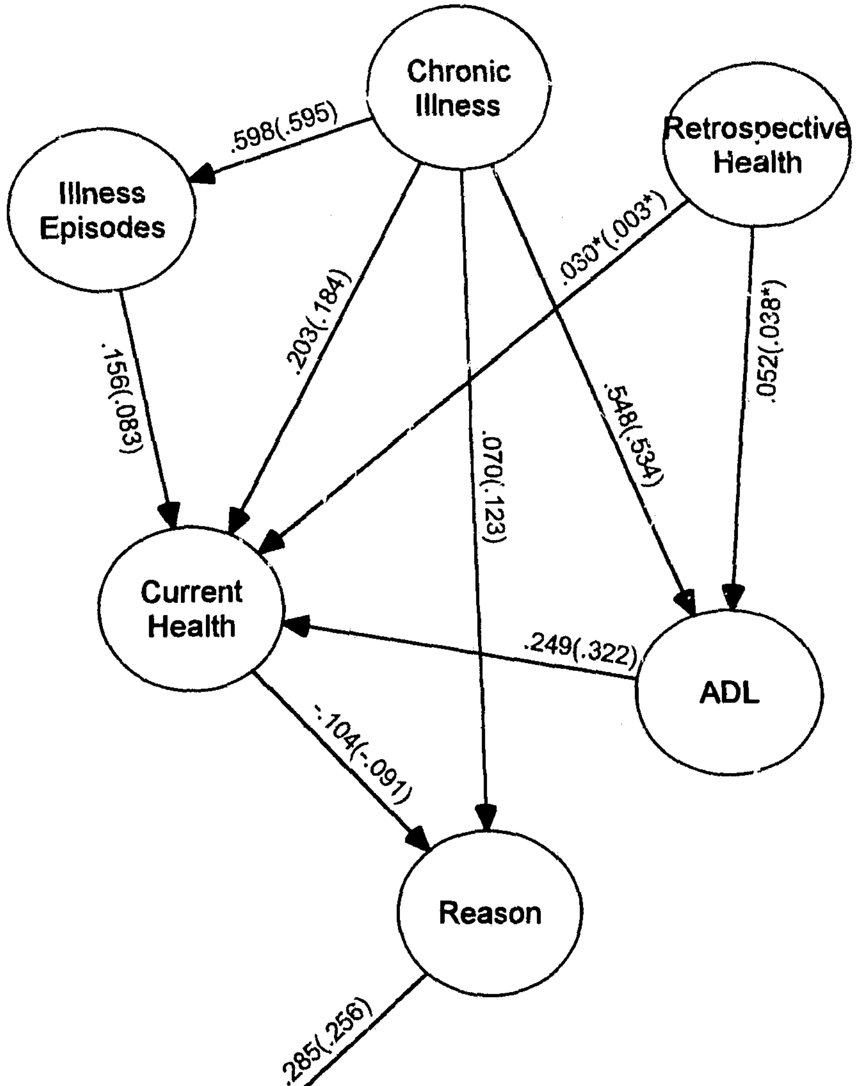

Figure 5

Final Self-rated Health and Cognition Structural Model with Sample 1 and Sample 2 estimates (Sample 2 in parentheses)

(* p > .05)

exhibit direct paths from the health measures. As expected, reasoning was a predictor of word recall. In addition to the direct effects of self-reported health on cognitive performance, several indirect paths were identified. Specifically, self-rated current health had a significant relationship to word recall that was mediated through reasoning (standardized parameter estimate: -.030). Similarly, a significant indirect path from chronic illness to reasoning, mediated by current health, was observed. In this case, the path was in the expected, negative, direction (-.045). Although self-reports of health ailments predicted significant portions of variance in word recall and reasoning, the absolute amount of variance accounted for is low.

In the next set of analyses, a cardiovascular illness factor was separated from the overall chronic illness factor. The was done in order to determine whether additional variance in word recall and reasoning could be accounted for by cardiovascular illness.

Self-rated Health, Cardiovascular Illness, and Cognitive Performance

Five variables were chosen to define the cardiovascular disease factor. These included: high blood pressure, medication for high blood pressure, visit to the doctor for heart ailments, and whether the participant had ever had a heart attack or heart surgery. Table 4 shows the mean, standard deviation, and skewness for the variables to be used in the models. The heart condition variables showed problems with distributional normality. This reflects the fact that relatively few participants had experienced these serious health conditions. Although problems of normality existed for these variables, they were thought to be critical to define the factor of cardiovascular illness, and were retained in subsequent models.

Table 10 presents the demographic and self-rated health characteristics of the two samples used to derive and replicated the measurement and structural models. A MANOVA comparing the demographic and self-rated health characteristics of the samples revealed no significant differences (Wilks' λ=.999, $F(5, 5044)$= .828, p= .530), indicating the random selection produced groups that were demographically comparable.

The initial measurement model that was tested used the final self-reported health measurement model that was derived earlier, and included the five-indicator cardiovascular illness factor. This model fit the data dismally ($\chi^2(103)$= 2377.79, p < .001, NFI= .813, CFI= .819). The source of the ill fitting model was the cardiovascular component, because all of the other factors were adequately represented in the previous measurement model. An inspection of the factor loadings for the cardiovascular factor revealed that the two blood pressure measures did not load highly on this factor (both loadings under .30). The other three measures all loaded above .50 on the factor. Moreover, the residual covariances indicated that the relationship between the two blood pressure variables was not well represented by the five-indicator factor. Based on these results, a second model was run in which the cardiovascular illness factor was separated into a blood pressure and heart disease component. This new model produced a very good fit to the data ($\chi^2(94)$= 413.19, p < .001, NFI= .968, CFI= .975, $\Delta\chi^2(9)$= 1964.60, p<.001).

Table 10

Demographic Characteristics of the Two Subsamples used to Devise and

Replicate the Cardiovascular Disease and Self-rated Health Models

Variable		Sample 1 N= 2525	Sample 2 N= 2525
Age	M	55.48	55.20
	SD	5.45	5.62
Gender[a]	M	1.56	1.56
	SD	.50	.50
Race[b]	M	1.24	1.24
	SD	.43	.43
Years of Education	M	12.28	12.33
	SD	3.02	3.02
Self-reported Health[c]	M	2.50	2.48
	SD	1.16	1.16

[a] Gender: 1= Male, 2= Female
[b] Race: 1= Caucasian, 2= Non-Caucasian
[c] Self-reported health on a 5-point scale (1= excellent to 5 = poor).

Table 11 presents the standardized factor loadings and communalities for this final model. As seen in the table, the eight non-cardiovascular factors all had significant loadings from their respective indicators. This replication of the factor structure for the self-rated health factors on this third random sample provides further evidence for the validity of the factor structure. Turning to the cardiovascular indices, both factors had significant and large (all above .50) loadings from their respective indicators. Both the blood pressure and the heart disease factors appeared to be well-defined. No other changes seemed warranted from an inspection of the residuals and modification indices, and this model was accepted as final.

Of course, before final acceptance of the measurement model can be made, the replicability of the parameters in an independent sample must be tested. The measurement model from the first sample was used as the basic model for both samples, and fit the data relatively well ($\chi^2(188) = 781.93$, $p < .001$, NFI= .969, CFI= .976). The constraints that the unstandardized factor pattern weights were equal across samples were added. Adding these constraints on the two samples did not significantly change the model fit ($\chi^2(196) = 793.17$, $p < .001$, NFI= .969, CFI= .976, $\Delta\chi^2(8) = 11.24$, $p > .05$). Although the overall fit was not significantly poorer, modification indices indicated that the loading of the variable indexing visits to the doctor for heart troubles on the heart disease factor was significantly different across the two samples. In Sample 3 the standardized factor loading was .836, whereas in Sample 4 the loading was .867. Although the loadings were significantly different, they did not appreciably change the identification of the heart disease factor,

Table 11

Standardized Factor Loadings and Communalities for the Ten Factor Self-Rated Physical Health, Cardiovascular Illness, Mental Health and Cognition Model

$\chi^2(94) = 413.26$, $p < .001$, NFI= .968, CFI= .975

Variable	Word Recall	Reasoning	Current Health	Retrospective Health	Illness Episodes	ADL	Chronic Illness	Communality
Immediate recall	.901							.811
Delayed recall	.869							.755
Similarities		.906						.821
current health			.947					.897
retrospective health				.946				.895
days in bed					.389			.151
doctor visits					.445			.198
ambulation						.682		.465
cardiovascular function						.591		.349
fitness						.491		.241
Chronic illness w/o CVD							.949	.901

Table 11 con't

Variable	Blood Pressure	Heart Disease	Mental Health	Communality
high blood pressure	.865			.748
blood pressure medication	.842			.709
heart attack		.749		.561
doctor for heart		.836		.699
heart surgery		.568		.323
Mental health rating			.778	.605
CES-D			.693	.480

and this difference was deemed to be a minor misspecification of the model. Therefore, based on these results it was concluded that the measurement model devised in the first sample fit the second sample as well, and the results were not simply due to chance. This measurement model was therefore used as the basis for the structural relations models that follow.

Table 12 presents the disattenuated factor correlations for the self-rated health, cardiovascular disease, mental health and cognitive factors. Because the relationships among the self-rated health and cognitive factors were described already (see Table 8), only the new, cardiovascular factors will be focused upon here. In general, the relationships among the cardiovascular disease and blood pressure factors were similar. Both factors were negatively related to performance on the cognitive measures, indicating that presence of cardiovascular illness is related to poorer cognitive performance. However, the amount of variance accounted for by the cardiovascular disease factors was modest, approximately .5% to 1.5% of variance. Similarly, both factors were positively related to the other indices of self-rated physical and mental health, indicating as incidence of cardiovascular illness increases, so do reports of other impairments with physical and mental health. In this case, the cardiovascular disease factors accounted for more variance in health ratings, ranging from 5% to 13%. Again, while these patterns of relationships are suggestive of cardiovascular disease, and other indices of physical health, moderating cognitive performance, the true relationship must be examined after controlling for potential confounds, such as education, age, gender, race, and mental health.

Table 12

Disattenuated Self-rated Physical Health, Cardiovascular Disease,

Mental Health and Cognitive Factor Intercorrelations

	Factor									
Factor	1	2	3	4	5	6	7	8	9	10
1. Word recall		.430	-.131	-.243	-.038*	.129	-.109	-.113	-.138	-.198
2. Reasoning	.429		-.115	-.317	-.003*	.159	-.203	-.101	-.130	-.269
3. Chronic illness	-.068	-.092		.601	.222	.510	.677	.259	.234	.495
4. Current health	-.217	-.292	.579		.217	.413	.676	.340	.356	.631
5. Retrospective health	-.052*	-.072	.162	.225		.148	.254	.072	.064	.313
6. Illness episodes	.126	.164	.509	.369	.080*		.543	.277	.463	.337
7. ADL	-.119	-.160	.649	.628	.245	.472		.291	.297	.603
8. Heart disease	-.068	-.078	.263	.357	.002*	.272	.257		.207	.190
9. Blood pressure	-.073	-.118	.224	.362	.006*	.327	.257	.245		.189
10. Mental health	-.192	-.253	.453	.647	.235	.322	.577	.204	.184	

All correlations are significant except where indicated * $p > .01$.
Note: Sample 3 values in lower triangle, Sample 4 in upper triangle.

Before turning to the structural analyses, the nonnormality of the cardiovascular and blood pressure variables warrants inspection. One option in the EQS structural relations program is the estimation of "robust" statistics (Bentler, 1989). Remember that nonnormal data may produce incorrect chi-square and standard error estimates. With robust statistics, the chi-square that is produced, the Satorra-Bentler chi-square (S-B χ^2, Satorra & Bentler, 1991) is corrected for multivariate kurtosis. Similarly, the standard errors that are produced are also corrected for deviations from normality. In the current case, the final measurement model was rerun, and robust statistics were requested. Comparing the χ^2 statistics, the Satorra-Bentler correction for nonnormality resulted in a decrease of almost 36 units ($\chi^2 = 413.19$ versus S-B $\chi^2 = 377.60$). Moreover, the robust standard errors that were produced were also slightly different from the original estimates. Although the robust statistics did produce slightly different values, they did not change the interpretation of the model. The S-B χ^2, while being slightly smaller in magnitude, was still statistically significant, and the other fit indices (NFI, CFI) did not change, because they are unaffected by variable normality. Similarly, the new, robust standard errors were not sufficiently different from the original estimates to change the interpretation of whether the loadings of variables on factors were statistically significant or not. Although the robust statistics produced by EQS are recommended by some (Hu et al., 1992), the implementation of these statistics can exact a heavy cost. In the current study, the time taken to estimate the robust statistics was almost 40 minutes, whereas the analysis that did not request these estimates took less than 1 minute! A recent monte carlo study by Hox (1995) noted that as the number of categorical variables to be estimated increased, the processing time required increased at an exponential rate. Therefore, although the robust statistics produced a slightly smaller χ^2 and improved standard error estimates, the processing time required, especially for the structural models, makes the consistent use of robust statistics unreasonable.

Figure 6 presents the base structural equation model for the new set of analyses. The structural model including the two cardiovascular disease components was essentially similar to the model that used the single chronic illness factor. The major change is that now, three factors (blood pressure, heart disease, chronic illness) take the place of the single chronic illness factor. In the new model, the relations between retrospective health are different in that retrospective health is thought to affect all new three factors. Similarly, the cardiovascular illness and chronic illness factors have paths to illness episodes, ADL, and current health. Finally, the relations among the three new factors were modeled differently. Specifically, blood pressure was thought of as a determinant of heart disease so this relationship was modeled as such. Relationships between blood pressure and heart disease and chronic illness were modeled as correlated residuals, because rather than blood pressure or heart disease 'causing' other chronic conditions, they may simply share variance that may be associated with having a long-term medical condition.

The initial structural model fit the data well ($\chi^2(141) = 572.16$, $p < .001$, NFI= .962, CFI= .971). An inspection of the parameter estimates revealed that the

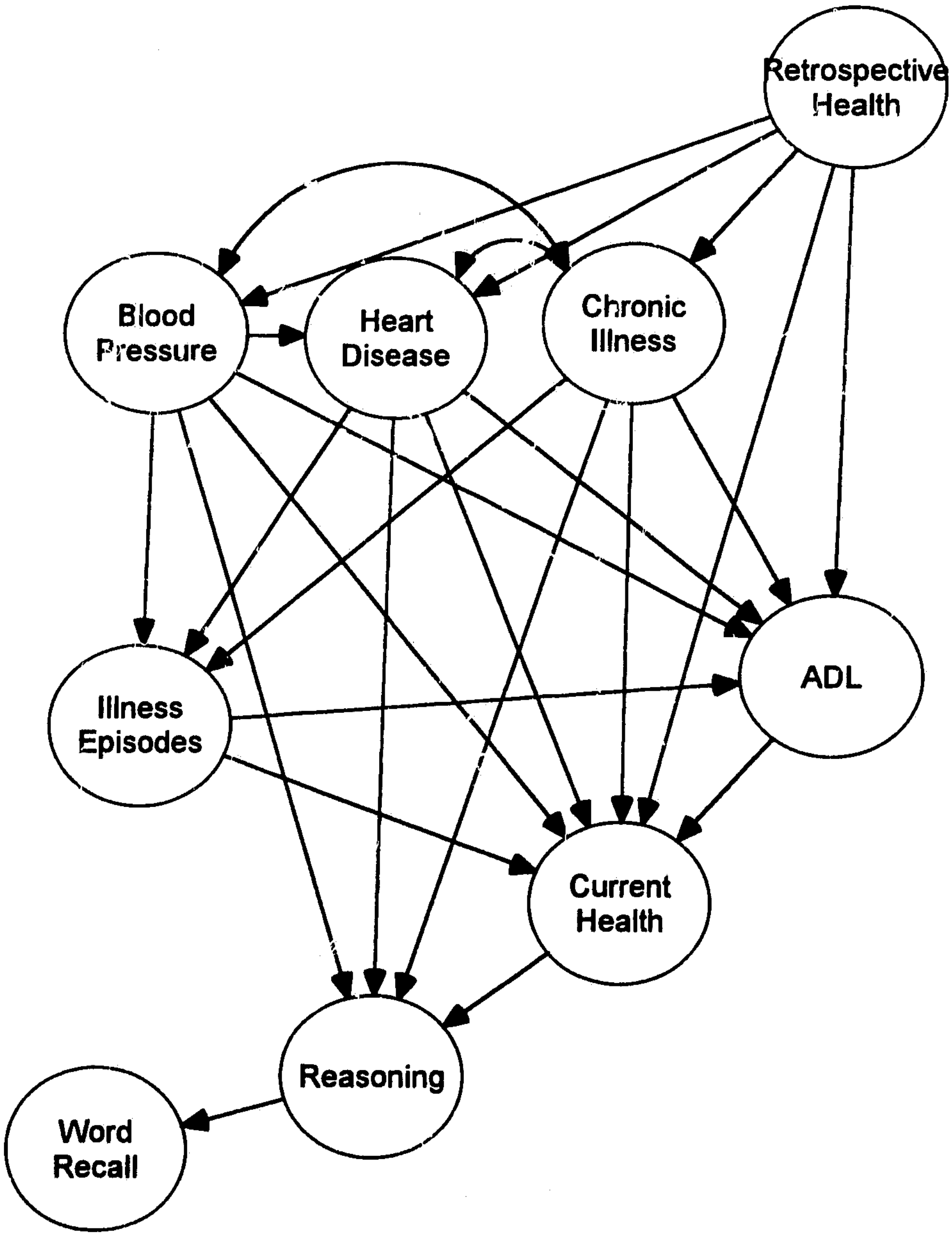

Figure 6
Revised Cardiovascular Health and Cognition Model
(Retrospective Health now included)

path from illness episodes to current health was non-significant (z= .91). This contrasts with the significant path between these variables that was observed in the previous self-reported health structural models. This nonsignificant path was retained in the model, and the significance of the path will be examined in the replication of the structural model with the other sub-sample. All other structural paths were statistically reliable. Inspection of the modification indices revealed that three paths could be added to the model to improve the fit. They were from illness episodes to reasoning, and word recall, and from illness episodes to ADL. The paths were added and the model was rerun. The addition of the paths significantly improved the overall fit of the model ($\chi^2(138)= 562.25$, $p < .001$, NFI= .962, CFI= .971, $\Delta\chi^2(3)= 9.91$, $p < .05$). Inspection of the parameter estimates revealed that although the addition of the three paths resulted in a significant decrease in chi-square, only one parameter estimate, from illness episodes to ADL, was statistically reliable. Therefore the paths from illness episodes to reasoning and word recall were eliminated and the model was rerun. This model produced a good fit to the data ($\chi^2(140)= 566.82$, $p < .001$, NFI= .962, CFI= .971, $\Delta\chi^2(2)= 4.57$, $p > .05$).

Next, the models that included paths from blood pressure and heart disease to reasoning were included. The model was designed to test Earles and Salthouse's (1995) result that the influence of self-rated health was mediated through cardiovascular disease only. This model produced a better, but not statistically better, fit to the data ($\chi^2(138)= 563.16$, $p < .001$, NFI= .962, CFI= .971, $\Delta\chi^2(2)= 3.66$, $p > .05$). Although the addition of the cardiovascular disease components did not significantly increase the overall fit of the model, they did result in the parameter from current health to reasoning becoming not statistically reliable (z= -1.282). Further, only one of the new parameters was statistically significant, that from blood pressure to reasoning; the path from heart disease to reasoning was not statistically reliable (z= -.82). The lack of a statistically significant path from Current Health to Reasoning indicates that this path is not a necessary component of the model. Hence, the data support Earles and Salthouse (1995) contention that cardiovascular illness, in this case blood pressure, was sufficient to model the physical health/cognition relationship. The nonsignificant paths, from Heart Disease and Current Health to Reasoning, were eliminated and the final model was run. This model produced a good fit to the data ($\chi^2(140)$= 565.45, p < .001, NFI= .962, CFI= .971, $\Delta\chi^2(2)$= 2.29, p>.05), and was considered to be the final model.

Before the structural model will be interpreted, the test of cross-validation will be reported. The final structural model was used as the basic model for both samples, and fit the data well ($\chi^2(280)$= 1121.65, p < .001, NFI= .962, CFI= .971). Next, the measurement model was constrained equal in both samples. Remember, the earlier cross-validation of the measurement model indicated that the loading of the variable indexing visits to the doctor for heart problems on the heart disease factor was not the same in both samples. Therefore, this loading was left unconstrained in the present context. This model fit the data well ($\chi^2(287)$= 1127.53, p < .001, NFI= .962, CFI= .971, $\Delta\chi^2(7)$= 5.88, p>.05). The next step was to run the model will all of the structural coefficients constrained to be equal. This model produced poorer, but not significantly poorer, fit to the data ($\chi^2(352)$= 1205.29, p < .001, NFI= .960, CFI= .971, $\Delta\chi^2(65)$= 77.76, p>.05). Although the overall fit of the model was not significantly poorer, modification indices revealed that several parameters were not equivalent across the two samples. These were (with standardized parameter estimates from sample 3 and sample 4 in parentheses): From Retrospective Health to Current Health (.048,-.012), from gender to Illness Episodes (.158,.302), from Mental Health to Retrospective Health (.248, .348), From Blood Pressure to Heart Disease (.199, .150), and from age to Blood Pressure (.135, .202). Among the parameters that were not equivalent, there were two that were of most concern, because they dealt with interrelations among factors. The relationship from Retrospective Health to Current Health actually changed sign across the two samples. However, in sample 3 the parameter is small and positive and in sample 4 the parameter is not statistically significant and negative. These differences are relatively minor, and reflect results that were seen in previous models, indicating that retrospective assessments of health status are not good predictors of current health ratings. The other non-equivalent parameters concerned the link between the two cardiovascular factors. In this case, the differences were also slight, and the parameters themselves were not large in magnitude. This was somewhat surprising given the expected relationship between high blood pressure and other cardiovascular conditions.

The relationships among the demographic control variables and the cardiovascular illness and self-reported physical health variables are presented in

Table 13. In the present context, the relationships to the new cardiovascular factors will be the focus here as the pattern of relationships for the self-reported health factors are similar to those discussed already (see Table 9). Both Heart Disease and Blood Pressure are positively related to age, and Mental Health. This indicates that as individuals get older, or report more problems with mental health, incidence of cardiovascular disease also increases. Race is negatively related to Heart Disease, but positively related to Blood Pressure, indicating caucasians exhibit greater incidence of heart disease, but fewer incidence of hypertension. Gender is negatively related to Heart Disease whereby women report fewer problems than men. Finally there is a small positive relationship between education and Blood Pressure.

Figure 7 shows the final structural model with parameter estimates from Sample 3 and 4. The pattern of relationships among the non-cardiovascular illness health measures essentially replicates those relations we have seen already. Retrospective health predicts chronic illness, ADL, and current health. Similarly, ADL predicts current health. Finally, chronic illness predicts illness episodes, current health and ADL. The relationships among the chronic illness are similar in direction to the previous analyses, but are somewhat attenuated in the absolute magnitude of the parameter coefficients. This could reflect elimination of variance in this measure by separating out the cardiovascular component, changes in parameters estimates due to the fact that different individuals are being used in this analysis, or both. Generally, the results are similar to those already presented.

Table 13

Standardized Parameter Coefficients for the Demographic Control Variables and the Self-Reported Physical Health, Cardiovascular Disease, and Cognitive Factors

	Demographic Control Variable				
Factor	Age	Gender	Race	Education	Mental Health
Word Recall	-.129	.160	-.125	.099	-.101
Reasoning	-.075	.080	-.185	.473	-.140
Current Health	.029*	-.098	.095	-.127	.342
Retrospective Health	.023*	-.054	-.070	-.046	.248
Illness Episodes	-.027*	.158	-.035*	.298	.141
ADL	.058	.144	-.051	-.100	.289
Chronic Illness	.114	.046	-.046	-.029*	.456
Heart Disease	.064	-.133	-.061	.001*	.210
Blood Pressure	.135	-.030*	.110	.051	.203

All estimates are significant except where indicated * $p > .05$.

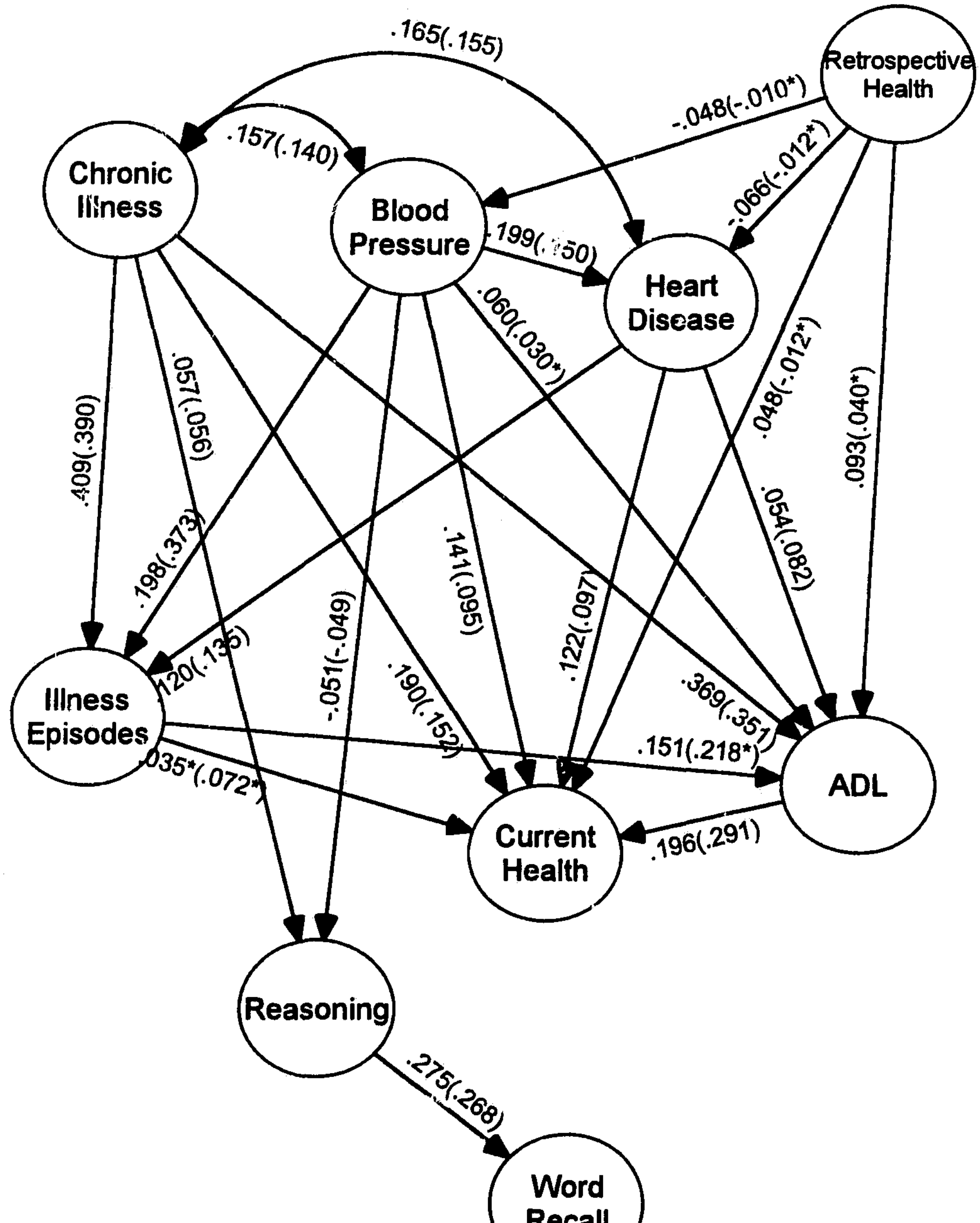

Figure 7
Final Cardiovascular Illness and Cognition Model with Sample 1 and Sample 2 estimates
(Sample 2 in parentheses)

(* p > .05)

Among the new cardiovascular measures, both Heart Disease and Blood Pressure correlate significantly with Chronic Illness. Further, Blood Pressure is a significant predictor of Heart Disease. Among the new cardiovascular measures, retrospective health exhibits only significant paths to these variables, only in Sample 3. Even then, the relationships are relatively small in magnitude. As such, it seemsthat the lagged assessment of health status is not a good predictor of current cardiovascular illness. Finally, both Blood Pressure and Heart Disease predict significant amounts of variance in illness episodes, current health and ADL.

Among the cognitive measures, reasoning shows the largest predictive relationships with self-reports of physical health. Blood Pressure is negatively related to reasoning performance, indicating that increased incidence of hypertension is associated with poorer reasoning performance. The magnitude of these relationships are relatively small in magnitude (.24% of variance). The only other direct predictor of cognitive performance is Chronic Illness, which exhibited a positive relationship to Reasoning. Again, this relationship is in the opposite direction to what was expected, and indicates that as incidence of chronic illness increases, so does reasoning performance. There is one additional parameter to note in the present model. This is an absence of a relationship between Current Health and Reasoning performance, as was seen in the previous analyses. The absence of this path is consistent with the findings of Earles and Salthouse (1995) and indicates that the predictive relationship to cognitive performance from physical health could be adequately represented without paths from overall health self-ratings.

In general, the relationships between cognitive performance and physical health have been very modest in terms of amount of variance accounted for. One possibility is that the because the current sample is younger than those that are typically used, the variety of health conditions that are observed may not be sufficient diverse to demonstrate a strong relationship between physical health and cognitive performance. To examine this possibility, an additional model was run in which the sample consisted of 969 individuals between the age of 62 to 83 years ($\underline{M}$= 65.06 years). This model provided a good fit to the data from the older sample ($\chi^2(140)$= 319.91, $\underline{p} < .001$, NFI= .942, CFI= .966). Examination of the standardized parameter estimates between the physical health and cognitive factors revealed little additional predictive power was gained by using the older sample. The path between chronic illness and reasoning was slightly larger in magnitude (standardized parameter estimate = .076), whereas the path between the blood pressure factor and reasoning was not statistically reliable (estimate = -.018) in the older sample. Therefore, it is not the case that the younger sample made it less likely that relationships between cognitive performance and physical health would be observed. Rather, it appears that, in the current study, there is little evidence for a strong predictive relationship between individuals' health status and their performance on tests of word recall and reasoning.

The lack of a predictive relationship may reflect the inadequate assessment of physical health by self-report measures. In the next section a set of objectively measured, physiologic indicators of health status will be incorporated. It may be the case that the ability to predict cognitive performance will be augmented by the physiological measures of health status.

Objective and Subjective Indicators of Health Status

Objective health measures were available only for a sub-samples of 500 individuals. These measures were in one of 10 modules administered to random samples of participants, hence the smaller number of respondents than usual. Because of the decrease in number of subjects, only a select number of health measures were included in the analyses, in order to limit the number of free parameters to be estimated. The choice of variables that were included was based on the previous predictive power of the health variables on cognitive performance. As a result, only measures of chronic illness and blood pressure were included in the following analyses. Although this results in an underidentification of the health concept, the focus of the present study is on the prediction of cognitive performance by health, and not the identification of health itself. Table 14 shows the mean, standard deviation, and skewness for all of the variables to be used in the objectively measured health models. Inspection of the table reveals no distributional problems associated with the objective measures of health status. Note that the values displayed in Table 14 are not adjusted for height and weight. In order to standardize the measures across participants, the values that are used in the structural equation models were residualized for gender, weight, and height, prior to model estimation. Further, the residualized values for grip strength and vital capacity were divided by 10, and 100,

Table 14

Mean, Standard Deviations, and Skewness of the Objectively Measured

Health Model Variables

(N= 500)

Variable	Mean	Standard Deviation	Skewness
Age	55.49	4.32	-.28
Gender	1.54	.50	-.14
Race	1.19	.39	1.59
Years of education	12.70	2.85	-.58
CES-D	15.46	3.89	1.16
Mental health	2.48	1.05	.23
Immediate word recall	7.87	2.50	.63
Delayed word recall	5.98	2.66	.82
Reasoning	6.41	2.95	-.04
Chronic illness excluding CVD	1.56	1.54	1.04
High blood pressure[a]	.39	.49	.47
Blood pressure medication[a]	.24	.43	1.20
Grip strength 1	82.01	30.48	.66
Grip strength 2	83.19	31.53	.70
Grip strength 3	83.68	31.71	.64
Vital capacity 1	401.95	141.69	-.22
Vital capacity 2	429.50	139.12	-.31
Vital capacity 3	439.47	134.32	-.34

[a] Variable dichotomized to indicated presence/absence of the condition. Higher scores indicate greater impairment

respectively, in order to scale the variances to the same magnitude as the other variables included in the measurement and structural models.

In order to develop the models, the sample was randomly divided into two equal size sub-samples (N=250). The first sub-sample was used to develop the measurement and structural models, while the second sub-sample was used to replicate the model parameters. Table 15 presents the demographic and self-rated health characteristics of the two sub-samples. A MANOVA comparing the demographic characteristics revealed no significant differences (Wilks' λ= .992, $F(5, 493)$= .632, p= .705), indicating that random selection created groups that were demographically comparable.

The measurement model consisted of seven latent variables. The seven factors were: Word Recall, Reasoning, Chronic Illness, Blood Pressure, Vital Capacity, Grip Strength, and Mental Health. The results of this analysis indicated that the model fit the data very well ($\chi^2(58)$= 76.52, p =.052, NFI= .969, CFI= .992). Inspection of the residual covariances and modification indices revealed no additional changes were needed. The standardized factor pattern weights and the estimated communalities are reported in Table 16. It shows that all measures had significant loadings on their respective factors. Note that the new objective health factors are particularly well defined, with loadings above .85.

Replication of the measurement model in the second sub-sample was the next task. The measurement model from the first sample was used as the basic model for both samples, and fit the data well ($\chi^2(116)$= 141.15, p = .056, NFI= .971, CFI=

Table 15

Demographic Characteristics of the Two Subsamples used to Devise and Replicate the Objectively Measured Health Models

Variable		Sample 1 N= 250	Sample 2 N= 250
Age	M	55.52	55.46
	SD	4.50	4.14
Gender[a]	M	1.53	1.54
	SD	.50	.50
Race[b]	M	1.22	1.16
	SD	.42	.37
Years of Education	M	12.70	12.70
	SD	2.86	2.85
Self-reported Health[c]	M	2.38	2.42
	SD	1.13	1.08
CES-D[d]	M	15.51	15.40
	SD	4.03	3.74

[a] Gender: 1= Male, 2= Female
[b] Race: 1= Caucasian, 2= Non-Caucasian
[c] Self-reported health on a 5-point scale (1= excellent to 5 = poor).
[d] Depressive symptomatology (11= none to 44= severe).

Table 16

Standardized Factor Loadings and Communalities for the Seven Factor Objectively-

Rated Physical Health, Mental Health and Cognition Model

$\chi^2(58) = 76.52$, $p = .052$, NFI= .969, CFI= .992

Variable	Word Recall	Reasoning	Mental Health	Chronic Illness	Blood Pressure	Grip Strength	Vital Capacity	Communality
Immediate recall	.940							.884
Delayed recall	.790							.624
Similarities		.941						.885
Mental health			.685					.469
CES-D			.791					.626
Chronic illness				.944				.891
Blood pressure medication					.748			.560
High blood pressure					.995			.990
Grip strength 1						.916		.839
Grip strength 2						.957		.916
Grip strength 3						.959		.920
Lung capacity 1							.887	.787
Lung capacity 2							.978	.956
Lung capacity 3							.950	.903

.995). The constraint that the unstandardized factor pattern weights be equal across samples were added. Adding this constraint on the two samples did not significantly change the model fit ($\chi^2(123) = 152.32$, $p = .038$, NFI= .968, CFI= .994, $\Delta\chi^2(7) = 11.17$, $p > .05$). Although the overall fit was not significantly poorer, modification indices indicated that the loading of the variable indexing medication for blood pressure on the Blood Pressure factor was significantly different across the two samples. In sample 1 the standardized factor loading was .748, whereas in Sample 4 the loading was .690. Although the loadings were significantly different, they did not appreciably change the identification of the Blood Pressure factor, and this difference was deemed to be a minor misspecification of the model. Therefore, based on these results it was concluded that the measurement model devised in the first sample, fit the second sample as well, and the results were not simply due to chance. This measurement model was therefore used as the basis for the structural relations models that follow.

Before turning to the structural relations models, the disattentuated factor correlations are presented in Table 17. Focusing on the new, objectively measured health factors, revealed several interesting patterns. Both Grip Strength and Vital Capacity were negatively related to other measures of physical and mental health. This indicates that better performance on the objectively measured characteristics was related to fewer reports of poor health. Turning to the cognitive measures, only Vital Capacity showed significant relationships to Word Recall and Reasoning. The relationships between the cognitive variables and Grip Strength were not statistically

Table 17

Disattenuated Objectively Measured Physical Health, Mental Health

and Cognitive Factor Intercorrelations

	Factor						
Factor	1	2	3	4	5	6	7
1. Word Recall		.457	-.018*	-.051*	.063*	.154	-.220
2. Reasoning	.424		-.041*	.055*	.085*	.301	-.325
3. Chronic illness	-.122*	-.062*		.224	-.196	-.103*	.415
4. Blood Pressure	-.082*	-.017*	.196		-.088	.004*	.191*
5. Grip Strength	.074*	.092*	-.163*	.005*		.144	-.105*
6. Vital Capacity	.176	.301	-.176	-.007*	.379		-.315
7. Mental Health	-.374	-.423	.395	.179*	-.284	-.316	

All correlations are significant except where indicated * $p > .01$.
Note: Sample 1 values in lower triangle, Sample 2 in upper triangle.

reliable. Next, we turn to the structural equation models that incorporated the new, objectively measured, indicators of physical health. One goal was to determine whether Vital Capacity still predicted cognitive performance after variance associated with age, gender, race, education, and mental health are taken into account.

Figure 8 presents the structural equation model that was fit to the data. All of the health variables were treated as correlates of each other, and no predictive relationship was modeled. This reflected the belief that the relationships among these particular variables are not necessarily causal in nature. Instead, the factors are modeled as correlated residuals. With respect to the prediction of Reasoning and Word Recall, Chronic Illness, Blood Pressure, and Vital Capacity were modeled as predictors of Reasoning performance. Based on the disattentuated factor correlations, no paths from Grip Strength to cognitive performance were included. Consistent with prior analyses, reasoning was modeled as a predictor of word recall.

The initial structural model fit the data well ($\chi^2(91)= 108.56$, $p = .101$, NFI= .960, CFI= .993). Inspection of the parameter estimates revealed that the paths from Blood Pressure and Grip Strength to Reasoning were not statistically significant ($z= .37$, $z= 1.51$, respectively). The model was therefore rerun after these nonsignificant paths were eliminated. This new model also produced a good fit to the data (($\chi^2(93)= 111.06$, $p = .098$, NFI= .959, CFI= .993, $\Delta\chi^2(2)= 2.5$, $p>.05$). Inspection of the modification indices and residual covariances suggested that no other changes were necessary.

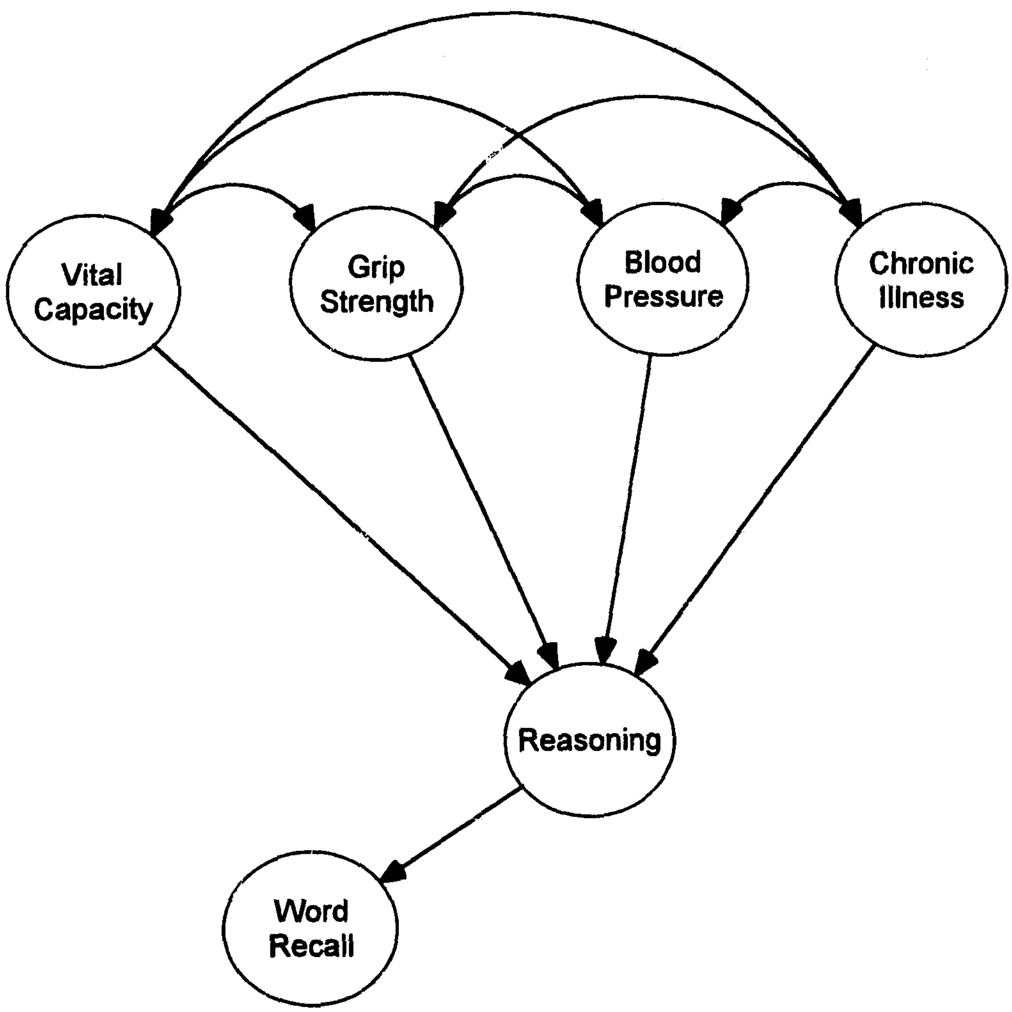

Figure 8
Revised Objectively-Rated Health and Cognition Model

Before interpreting the structural model, an attempt to replicate the same structure on the second sub-sample was made. The final structural model fit both samples relatively well ($\chi^2(186) = 216.30$, $p = .063$, NFI= .959, CFI= .994). Constraining the measurement model to be equal in both samples did not degrade the fit significantly ($\chi^2(192) = 224.49$, $p = .054$, NFI= .957, CFI= .993, $\Delta\chi^2(6) = 8.19$, $p > .05$). Finally, the analysis that constrained all structural pattern coefficients the same in both samples also did not degrade the fit significantly ($\chi^2(224) = 245.85$, $p = .151$, NFI= .953, CFI= .996, $\Delta\chi^2(32) = 21.36$, $p > .05$). In addition, the modification indices revealed that all parameter estimates were consistent across the two samples.

The relationships among the demographic control variables and the physical health and cognitive measures are presented in Table 18. Both of the objectively measured health status indicators were negatively related to age and mental health. This indicates that increased age and more reports of problems with mental health were associated with poorer performance on the measures of grip strength and vital capacity. Further, more years of education was associated with better performance on the tests of vital capacity, but not with grip strength. All other relationships expressed in Table 18 were consistent with previous results.

The final objectively measured health and cognition model, and parameter estimates, are presented in Figure 9. Focusing on the health measures first, there is very little correlation among the different indicators of health status. Chronic Illness is positively correlated with Blood Pressure, and negatively correlated with Grip

Table 18

Standardized Parameter Coefficients for the Demographic Control Variables and the Objectively Measured Physical Health, and Cognitive Factors

	Demographic Control Variable				
Factor	Age	Gender	Race	Education	Mental Health
Word Recall	-.112*	.213	-.055*	.310*	-.217
Reasoning	-.040*	.035*	-.143	.425	-.267
Chronic Illness	.061*	.122*	-.067*	-.042*	.389
Blood Pressure	.034*	.051*	.039*	.102*	.217
Grip Strength	-.150	-.044*	.009*	-.001*	-.276
Vital Capacity	-.126	.057*	-.062*	.182	-.245

All estimates are significant except where indicated * $p > .05$.

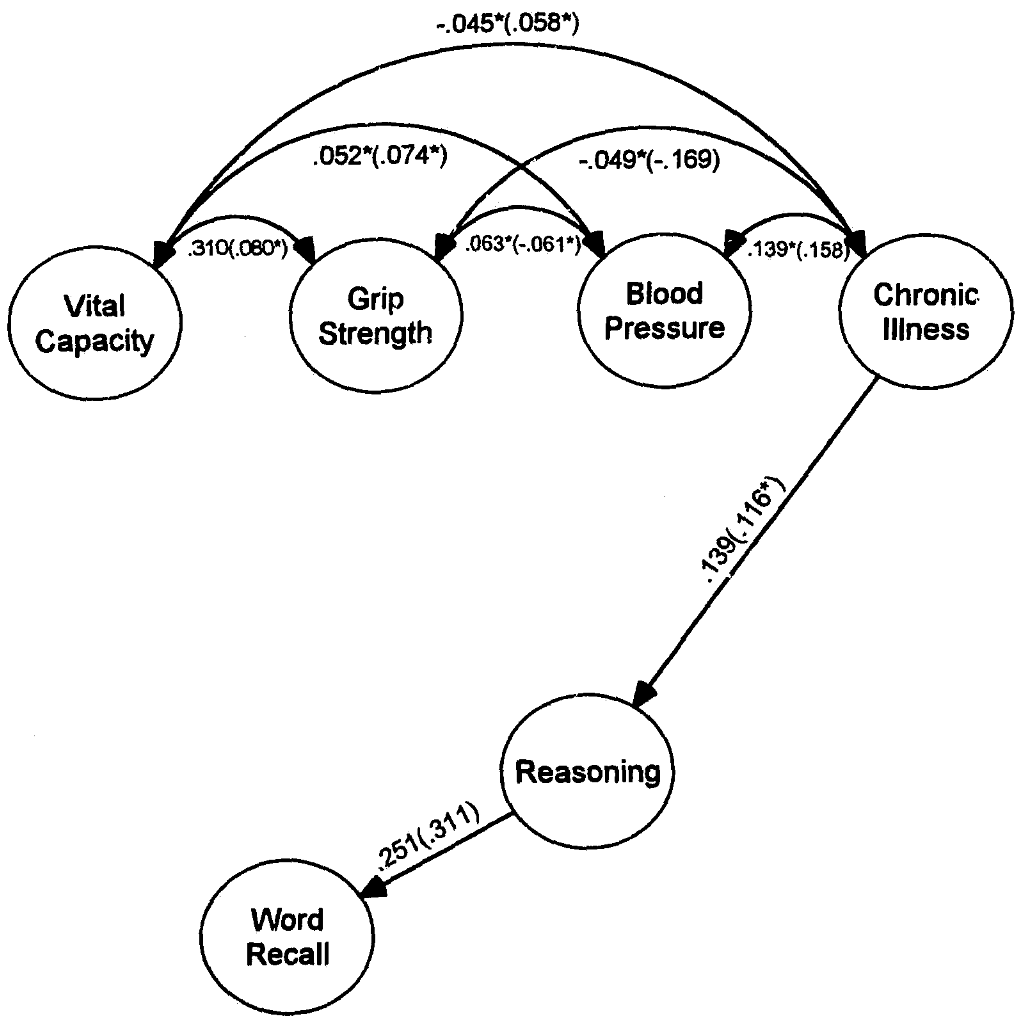

Figure 9
Final Objectively-Rated Health and Cognition Model with Sample 1 and Sample 2 Estimates
(Sample 2 in parentheses)

(* p > .05)

Strength. The only other significant correlation was a positive between Vital Capacity and Grip Strength, and this was significant only in Sample 1. The lack of relationship between Vital Capacity and Grip Strength is somewhat surprising given these measures are both physiological indices of health status. This suggests that although the two health factors are measured objectively, they do not necessarily tap into the same health construct. In general, there is little relationship among the four measures, all presumed to be indices of physical health. Among the cognitive measures, Reasoning was a strong predictor of Word Recall. However, only one path from the health measures to cognitive performance was significant, a path from Chronic Illness to Reasoning in Sample 2. Further, this path was positive indicating that with more incidence of chronic illness, reasoning scores increase. This paradoxical relationship replicates those results found in the other self-rated health structural models.

Summary

In general, there is no evidence for large portions of variance in cognitive performance being predicted by differences in individual health status. Where significant, the health variables predict modest amounts of variance in Reasoning (2% in the self-rated health models, .5% in the self-rated health and cardiovascular disease models, and 1.5% in the models with objectively measured indicators of health status), and exhibit no direct predictive relationship with word recall. Of all health related factors, Mental Health predicted the greatest amounts of variance in cognitive performance. In the self-rated health models, Mental Health predicted roughly 1% of the variance in word recall and reasoning performance. Similarly, in the models with cardiovascular disease, Mental Health predicted between 1-2% of the variance in cognitive performance. Finally, in the models that incorporated the objectively measured health factors approximately 4.5% of the variance in word recall, and 7% of the variance in reasoning was predicted by differences in Mental Health.

The lack of a predictive relationship between physical health and cognitive performance has implications for the next set of analyses on occupational complexity. Remember that the structural models including occupational complexity were going to include self-rated health characteristics in order to control for the potential contribution of health status to cognitive performance. As the analyses above indicate, there is no evidence of a strong relationship between health status and word recall and reasoning. In the next set of models, instead of including factors related to physical health, only a mental health factor will be included as a potential health-related confound to cognitive performance.

Occupational Complexity and Cognitive Performance

In the next section, the focus turns from health related predictors of cognitive performance, to those related to the complexity of an individuals work environment. First, the occupational complexity factors will be identified by self-report ratings. Next, the relationship between occupational complexity and cognitive performance will be assessed with standardized ratings.

Self-rated Occupational Complexity Measurement and Structural Models

Table 19 shows the means, standard deviations, and skewness for all of the variables to be used in the self-reported occupational complexity models. The sample consisted of individuals who were currently employed. As seen in the table, the new self-rated occupational complexity variables exhibited no problems with distributional normality. One variable, inquiring about the extent of lifting required by the job, was slightly skewed, but in general the variables were normally distributed. In order to develop the structural equation models, the sample was randomly divided into two equal size sub-samples (N= 2731). The first sample was used to develop the measurement and structural models, whereas the second sample was used to replicate the parameter estimates. Table 20 presents the demographic, occupational and self-rated mental health characteristics of the sub-samples. A MANOVA comparing the demographic characteristics of the two sub-samples revealed no significant differences (Wilks' λ=.999, $F(6, 5455)$= .723, p= .631), indicating the random selection created groups that were demographically comparable.

Before the results from the measurement models are described, one concern with the use of self-report indices of occupational complexity must be addressed. One potential problem with the self-report measures of occupational demand deals with individuals perceptions of the demands they face in the workplace. For example, two individuals may rate their jobs as having a high memory demand. However, one individual could be classified as having an unskilled job, whereas the other may be considered to be in a professional occupation. Clearly, the way that occupational

Table 19

Mean, Standard Deviations, and Skewness of the Self-rated

Occupational Complexity Model Variables

(N= 5462)

Variable	Mean	Standard Deviation	Skewness
Age	54.51	5.15	-.65
Gender	1.55	.50	-.20
Race	1.24	.43	1.19
Years of education	12.74	2.87	-.73
Occupation	2.73	1.32	-.06
CES-D	15.16	3.80	1.72
Mental health	2.40	.99	.27
Immediate word recall	7.88	2.56	.59
Delayed word recall	5.98	2.63	.70
Reasoning	6.44	2.95	-.01
Years experience	16.20	12.20	.47
Physical	2.24	1.11	.37
Lifting	1.66	.93	1.34
Stooping	2.01	.99	.74
Compute	2.08	1.22	.59
Data	2.31	1.19	.26
Repetitious	2.94	1.01	-.45
Freedom	2.91	.99	-.56
Learn	2.66	.98	.03
Memory	3.23	.60	-.36
Difficult	2.59	.79	.12

Table 20

Demographic Characteristics of the Two Subsamples used to Devise and Replicate the Self-rated Occupational Job Complexity Models

Variable		Sample 1 N= 2731	Sample 2 N= 2731
Age	M	54.49	54.42
	SD	5.18	5.12
Gender[a]	M	1.55	1.55
	SD	.50	.50
Race[b]	M	1.25	1.24
	SD	.43	.43
Years of Education	M	12.71	12.77
	SD	2.90	2.83
Self-reported Mental Health[c]	M	2.42	2.37
	SD	1.00	.98
Occupation[d]	M	2.75	2.71
	SD	1.32	1.33

[a] Gender: 1= Male, 2= Female
[b] Race: 1= Caucasian, 2= Non-Caucasian
[c] Self-reported mental health on a 5-point scale (1= excellent to 5 = poor).
[d] Rated on a 5-point scale (1= professional, 2 = semiprofessional, 3 = skilled, 4 = semiskilled, and 5 = unskilled).

complexity is conceptionalized in the present study, one would expect that ratings of cognitive demands of work to be higher in professional occupations and higher ratings of physical dimensions of work would be associated with less skilled occupations. One way to test this idea is to correlate the ratings of occupational complexity with a classification of occupation type. Table 21 presents the correlations between occupational complexity and the five-point job code scale. As shown in the table, positive correlations were present for the physical demand, lifting, stooping, and repetitious nature of work. This indicates that less skilled occupations were associated with higher physical demands and repeated aspects of work. On the other hand, use of computers, analyzing data, occupational freedom, learning new things, memory demands and doing difficult work was negatively associated with job classification. This indicates that more professional occupational are associated with these demands that can be considered more intellectual in nature. Thus, the concern that individuals' perceptions of occupational demand may lead to inaccurate ratings of complexity of work is somewhat diminished.

The first task was to develop a measurement model for the self-reported occupational characteristics and cognitive latent variables. A 7-factor model was hypothesized for the self-report occupational complexity and cognitive latent variables. The latent variables (with measured variables in parentheses) were: Word Recall (immediate and delayed word recall), Reasoning (word similarities), Mental Health (CES-D, self-rated mental health), Physical Demands (physical, lifting, stooping), Data (work with computers, analyze data or information), Freedom

Table 21

Correlation of Occupation Classification and Occupational Complexity

Occupational Complexity	Occupational Classification[a]
Physical	.349
Lifting	.292
Stooping	.258
Computer use	-.303
Analyze data	-.445
Repeat	.315
Freedom	-.216
Learn new things	-.288
Memory demands	-.207
Difficult	-.206

[a]Rated on a 5-point scale (1= professional, 2 = semiprofessional, 3 = skilled, 4 = semiskilled, and 5 = unskilled).

(repeated actions, freedom to decide about work), and Mental Demands (requires a good memory, learn new things, do difficult things).

The initial measurement model fit the data relatively well ($\chi^2(70) = 329.41$, $p < .001$, NFI= .969, CFI= .975). The standardized factor loadings and estimated communalities are reported in Table 22. An inspection of the table reveals that all measures had significant loadings on their respective factors. One of the factors, Freedom, was not well defined, with loadings accounting for only 21% and 12% in their respective indicator variables. Nevertheless, these loadings were statistically reliable, and modification indices or residual covariances offered no suggestions on how to better define this factor. Also note that the Freedom factor was defined by a positive loading from repetitiousness of work, and a negative loading from the extent to which the job afforded freedom to decide how work was done. As a guide to interpreting relationships with this factor, positive relationships indicated increases in repetitious aspects of work. Therefore, this measurement model was accepted as final.

The next step was to determine whether the measurement model defined in the first sub-sample would be replicated in the second sample. The measurement model from the first group was used as the basic model for both samples and fit the data well ($\chi^2(140) = 733.77$, $p < .001$, NFI= .965, CFI= .971). Next, the constraints that the unstandardized factor pattern weights were equal across the samples was added. Adding these constraints on the two samples did not significantly change the fit of the model ($\chi^2(148) = 741.67$, $p < .001$, NFI= .965, CFI= .971, $\Delta\chi^2(8) = 7.9$,

Table 22

Standardized Factor Loadings and Communalities for the Self-Reported Occupational

Complexity, Mental Health and Cognition Model

$\chi^2(70) = 329.41$, $p < .001$, NFI= .969, CFI= .975

Variable	Word Recall	Reasoning	Mental Health	Physical Demand	Data	Freedom	Mental Demand	Communality
Immediate recall	.910							.828
Delayed recall	.857							.734
Similarities		.917						.841
Mental health			.848					.719
CES-D			.584					.341
Physical				.814				.663
Lifting				.812				.659
Stooping				.727				.529
Computer use					.677			.458
Analyze data					.814			.663
Repeat						.456		.208
Freedom						-.346		.120
Learn new things							.647	.419
Memory demands							.495	.245
Difficult							.513	.263

$p > .05$). Although the overall fit of the model was not statistically different, modification indices revealed that the loading of the variable indexing the extent to which the job required stooping on the Physical Demand factor was significantly different across the two samples. In sample 1 the standardized factor loading was .727, whereas in sample 2 the loading was .764. Although the loadings were significantly different, they did not appreciably change the identification of the Physical Demand factor, and this difference was deemed a minor misspecification of the model. Therefore, based on these results it was concluded that the measurement model devised in the first sample, fit the second sample as well, and the results were not simply due to chance.

Table 23 presents the disattenuated factor correlations for the self-rated occupational complexity, mental health, and cognitive factors. Among the relationships with cognitive performance, all of the occupational complexity factors showed strong and significant relationships. Reasoning, in particular, showed large correlations with measures of occupational complexity. Occupations with high physical demands, and little freedom to decide how work was conducted was related to poorer word recall and reasoning performance. On the other hand, occupations that had high mental demands, or required individuals to analyze data or use computers, were positively related to cognitive performance. Among the occupational complexity factors, several strong relationships emerged. One in particular, the correlation between the Data and Mental Demands factors, was especially large in magnitude (.638 in sample 1, and .699 in sample 2). This large correlation motivated

Table 23

Disattenuated Self-rated Occupational Complexity, Mental Health and Cognitive Factor Intercorrelations

	Factor						
Factor	1	2	3	4	5	6	7
1. Word Recall		.410	-.124	-.190	.227	-.295	.129
2. Reasoning	.411		-.216	-.269	.325	-.583	.156
3. Mental Health	-.147	-.254		.125	-.143	.439	-.064*
4. Physical Demand	-.157	-.318	.132		-.447	.520	-.080
5. Data	.235	.350	-.165	-.427		-.465	.699
6. Freedom	-.181	-.481	.449	.526	-.406		-.393
7. Mental Demand	.137	.174	-.097	-.030*	.638	-.274	

All correlations are significant except where indicated * p > .01.
Note: Sample 1 values in lower triangle, Sample 2 in upper triangle.

an additional measurement model to be tested. In this model, the Data and Mental Demand factors were modeled with a higher-order factor. However, this model produced a significant decrement in fit ($\chi^2(75) = 542.53$, $p < .001$, NFI= .949, CFI= .955, $\Delta\chi^2(5) = 213.12$, $p < .001$). Therefore, based on these results, and those of the sample cross-validation, the measurement model with the four single-order occupational complexity factors was used as the basis for the structural relations models that follow.

The base structural model for the self-rated occupational complexity indicators is presented in Figure 2. The multiple aspects of occupational complexity were modeled as correlated disturbances. This reflected the belief that the occupational complexity factors were co-related, rather than being causally related. Further the four occupational complexity factors were modeled as influencing Reasoning directly, but only influencing Word Recall indirectly. This reflects the belief that the abstract reasoning measure may capture the types of occupations that are performed in the work environment. Finally, each of the cognitive and occupational complexity factors received paths from the demographic control variables: Age, gender, race, education, occupational experience, and Mental Health. The initial structural model fit the data well ($\chi^2(114) = 538.83$, $p < .001$, NFI= .959, CFI= .967). Inspection of the parameter estimates revealed that the path from Physical Demand to Reasoning, as well as the path from Mental Demand to Reasoning were not statistically reliable (z= .811, z= -1.50, respectively). These paths were eliminated and the model was rerun. The new model also produced a good fit to the data ($\chi^2(116) = 541.38$, $p < .001$, NFI= .959, CFI= .967, $\Delta\chi^2(2)$= 2.55, p > .05). Inspection of the modification indices revealed that the addition of a path from Data to Word Recall would improve the overall fit of the model. This path was added and the resultant model produced a significantly better fit to the data ($\chi^2(115)$= 536.46, p < .001, NFI= .959, CFI= .968, $\Delta\chi^2(1)$= 4.92, p < .05). However, with addition of this new path, the path from Data to Reasoning was no longer statistically reliable (z= 1.89). Therefore, one final model was run in which this path was eliminated. This model fit the data well ($\chi^2(116)$= 539.71, p < .001, NFI= .959, CFI= .967, $\Delta\chi^2(1)$= 3.25, p > .05), and an inspection of the modification indices and residual covariances revealed that no additional modifications were necessary.

Before the final structural model was interpreted, the replicability of the structural parameters was assessed. The final structural model was used as the basic model for both samples, and fit the data well ($\chi^2(232)$= 1213.28, p < .001, NFI= .954, CFI= .962). Next, the measurement model was constrained to be equal in both samples. In this case, because of the significant modification parameter found in the measurement model cross-validation, the loading of the stooping variable on the Physical Demand factor was not constrained equal across both samples. This model fit the data well ($\chi^2(239)$= 1219.76, p < .001, NFI= .954, CFI= .962, $\Delta\chi^2(7)$= 6.48, p > .05). The final set of constraints involved the structural parameters themselves. This model also produced a good fit to the data ($\chi^2(278)$= 1250.82, p < .001, NFI= .953, CFI= .963, $\Delta\chi^2(39)$= 31.06, p > .05). Although the overall fit was not significantly poorer, modification indices revealed that releasing the equivalence constraint for one of the structural parameters would decrease the chi-square by almost 6 units. Specifically, the path from education to Reasoning was not equivalent across the two samples. In sample 1, the standardized path coefficient was .299, whereas in sample 2 the parameter was .372. Although this parameter was not equivalent across the two samples, the path did not involve any of the parameters among the cognitive or occupational complexity factors, and was therefore deemed to be a relatively minor misspecification of the model.

The relationships among the demographic control variables, mental health, cognitive and occupational complexity factors are presented in Table 24. Among the occupational complexity factors, gender and education were negatively related to Physical Demands of a work environment. This indicated that men, and individuals with fewer years of education, were more likely to work in physically demanding occupations. On the other hand, caucasians, or individuals with better self-reported mental health, were more likely to in occupations that did not stress physically demanding activities. With respect to dealing with data, women, and individuals with more years of education or more years of occupational experience were more likely to work in environments that involved dealing with data. In contrast, older adults, non-caucasians or people with poorer mental health were less likely to analyze data as part of their occupations. As for work environments that allowed for little freedom to decide upon how work was done, women, non-caucasians, and individuals with poorer mental health were more likely to be in these occupations, as compared to individuals with more years of education, or years of occupational experience.

Table 24

Standardized Parameter Coefficients for the Demographic Control Variables and the Self-rated Occupational Complexity, and Cognitive Factors

	Factor					
Control Variable	Word Recall	Reasoning	Physical Demand	Data	Freedom	Mental Demand
Age	-.107	-.056	-.033*	-.086	.029*	-.097
Gender	.177	.197	-.064	.084	.294	.035*
Race	-.110	-.161	.041	-.089	.159	.017*
Education	.085	.299	-.350	.380	-.403	.264
Occupational Experience	-.013*	-.052	.009*	.091	-.112	.156
Mental Health	-.057	-.028*	.033	-.058	.263	-.029

All estimates are significant except where indicated * $p > .05$.

Finally, mentally demanding occupations were more likely to be occupied by younger individuals, with more years of education or more years of occupational experience.

The final self-reported occupational complexity and cognition model, and parameter estimates from sample 1 and 2, are presented in Figure 10. Focusing on the relationships among the occupational complexity factors, several interesting results emerge. Both of the factors that index negative aspects of a work environment, physical demand, lack of freedom, are positively related, as are the factors that measure the positive aspects of an occupation, dealing with data, mental demands. The relations across the two classes of occupational complexity factors are generally negative, with the exception of a small positive correlation between physical and mental demands. Among the cognitive measures, Reasoning was predicted by the Freedom factor. Freedom predicted between 7% (sample 2) and 12% (sample 1) of Reasoning performance. This indicated that individuals who work in occupations that allow freedom to decide how work is done performed better on the word similarities measure as compared to individuals who work in more closed environments. The only additional occupational complexity measure that predicted cognitive performance was Data on Word Recall. However, the amount of variance that this predictor accounted for was relatively small, less than .5%, and this path was not statistically reliable in sample 2. Thus, it appears that the types of demands, either physical or mental, that are placed upon an individual in his or her work environment are not as important as the initiative that workers are allowed to display in deciding the types of work tasks they perform.

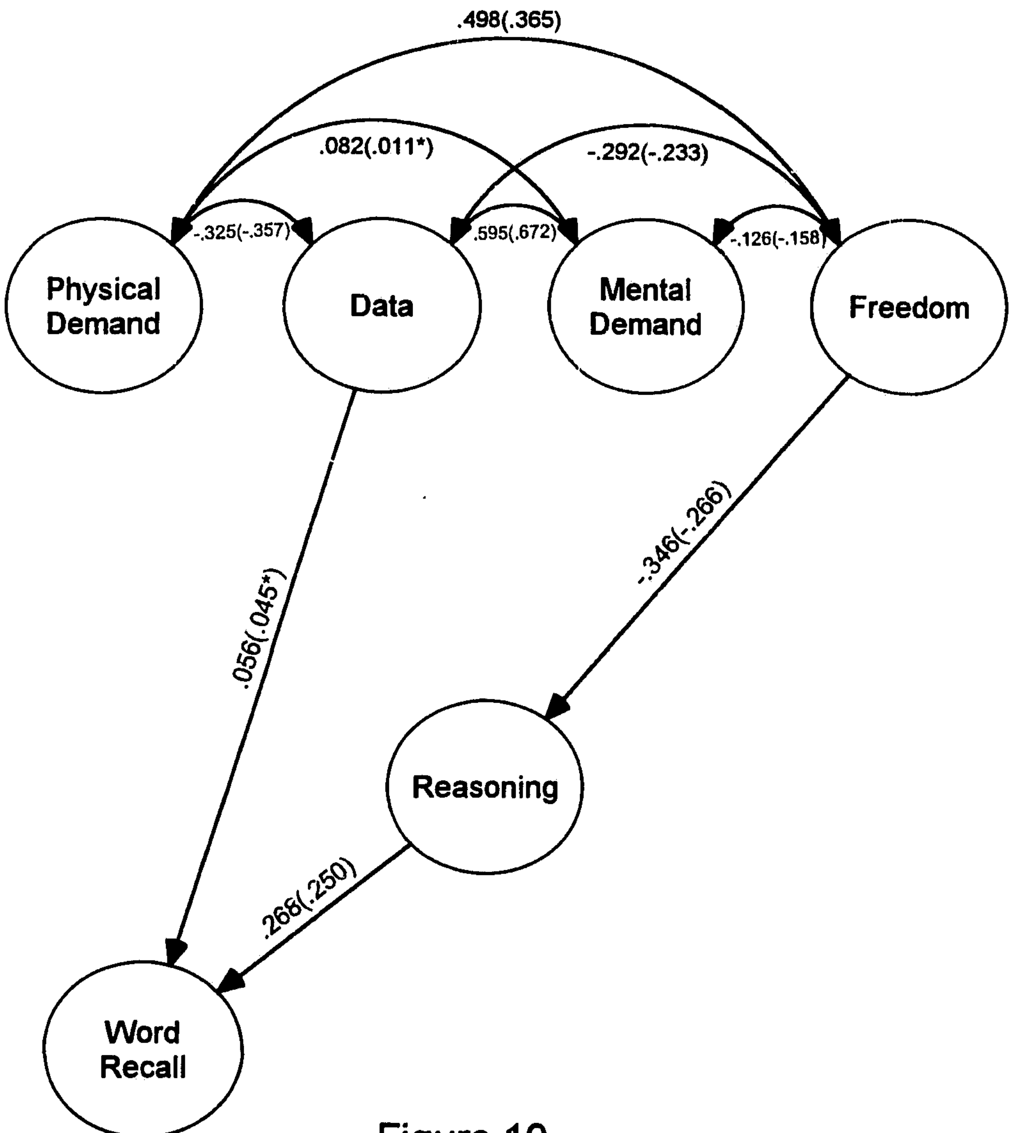

Figure 10
Final Self-Rated Occupational Complexity and Cognition Model with Sample 1 and Sample 2 Estimates
(Sample 2 in parentheses)

(* p > .05)

One additional set of models were run in which individuals with more or less than one year of occupational experience were used as the samples. These models were designed to test whether individuals who are new to an occupation, in what Murphy (1989) describes as the transition phase, would exhibit a stronger relationship between occupational complexity and cognitive performance. Essentially, the procedure used to test this hypothesis was similar to the cross-validation procedure of the model parameters. The constrained measurement and structural model parameters were compared across the two samples, those with more or less than one year of occupational experience, and the fit of these parameters was assessed. Note that experience was operationally defined as the number of years in a particular occupation, which may not necessarily be the same as the number of years with the same employer. For instance, an individuals may maintain their current occupation for a number of years, but change for whom they work for several times. It is expected that the skills demanded by a particular occupation would remain consistent across different work settings, hence the reason for measuring experience as the number of years in the current occupation.

The demographic characteristics of the samples with more or less than one year of occupational experience are shown in Table 25. A MANOVA indicated that the samples were not comparable demographically (Wilks $\lambda = .978$, $F(6, 4455) = 20.41$, $p < .001$). In particular, individuals who were employed for 1 year or less tended to be younger ($F(1,5460) = 27.98$, $p < .001$), were more likely to be female ($F(1,5460) = 19.88$, $p < .001$), had fewer years of education ($F(1,5460) = 10.16$,

Table 25

Demographic Characteristics of the Self-rated Occupational Complexity Sub-samples who were Currently Employed for Up to or More Than 1 Year

		Length of Employment	
		Up to 1 year	More than 1 year
Variable		N= 531	N = 4931
Age	M	53.38	54.63
	SD	5.93	5.05
Gender[a]	M	1.64	1.54
	SD	.48	.50
Race[b]	M	1.24	1.24
	SD	.43	.43
Years of Education	M	12.36	12.78
	SD	3.10	2.84
Self-reported Mental Health[c]	M	2.52	2.38
	SD	1.02	.98
Occupation[d]	M	3.19	2.68
	SD	1.24	1.32

[a] Gender: 1= Male, 2= Female
[b] Race: 1= Caucasian, 2= Non-Caucasian
[c] Self-reported mental health on a 5-point scale (1= excellent to 5 = poor).
[d] Rated on a 5-point scale (1= professional, 2 = semiprofessional, 3 = skilled, 4 = semiskilled, and 5 = unskilled).

$\underline{p}$=.001), occupied less prestigious occupations ($\underline{F}(1,5460)= 72.84$, $\underline{p}<.001$), and rated their mental health as being slightly poorer ($\underline{F}(1,5460)= 9.21$, $\underline{p}=.002$). Although both samples were not comparable demographically because the structural analyses assess relationships independent of these confounding variables, differences among the self-rated occupational characteristics and cognitive performance resulting from demographic differences were not expected.

The structural model that was fit to the samples used the final model produced above, with one exception. Because the models were designed to test the influence of occupational experience on the occupational complexity/cognition relationship, this variable was not used as a control variable in the structural models. The initial, unconstrained, structural model fit the data relatively well ($\chi^2(216)= 1171.83$, $\underline{p}$ < .001, NFI= .954, CFI= .962). Next, the measurement model was constrained to be equal across both samples. This model produced a significant decrement in fit ($\chi^2(223)= 1191.28$, $\underline{p}$ < .001, NFI= .954, CFI= .962, $\Delta\chi^2(7)= 19.45$, $\underline{p}$ < .01). Examination of the modification indices revealed that three constraints could be released to improve the fit of the model. Specifically, the factor loading of the variable indexing the extent to which the job required lifting on the Physical Demand factor was significantly larger in the sample of individuals employed one year or less (.876 versus .806). Similarly, the loading of the variable indexing occupational memory demands on the Mental Demand factor was significantly larger in the sample with fewer years of occupational experience (.590 versus .472). On the other hand, the sample of individuals with more years of experience had a higher loading of the variable indexing whether the job required more difficult things on the Mental Demand factor (.492 versus .477). Therefore, there is some evidence that at least the factor structure of the items may not be exactly the same across the two samples. The constraints on the significantly different parameters were released and the constrained measurement model analysis was rerun. In this case, the change in fit was not statistically significant ($\chi^2(220) = 1174.49$, $p < .001$, NFI= .954, CFI= .962, $\Delta\chi^2(4) = 2.66$, $p > .05$).

In the next model, the structural parameters were constrained equal across the two samples. This model also produced a significant decrement in fit ($\chi^2(253) = 1226.15$, $p < .001$, NFI= .952, CFI= .962, $\Delta\chi^2(33) = 51.66$, $p < .05$). The source of the ill-fitting model was the constraint of two parameters dealing with the demographic control variables. In the sample with greater occupational experience, the path from race to the occupational complexity factor Freedom was significantly larger than the same path in the sample with fewer years of experience (.171 versus .040). On the other hand, the sample with fewer years of experience had a significantly larger negative relationship between age and Mental Demands (-.227 versus -.056). Although the model did produce a significant decrement in fit, the source of the poor fit was not located among the occupational complexity or cognitive factors. Therefore, there is little evidence that length of tenure in an occupation decreases, or increases, the relationship between occupational complexity and cognitive performance.

In the next set of analyses, the DOT job complexity code (US Department of Labor, 1977) were used as indicators of occupational complexity. The was done to determine whether more objective indices of occupational complexity would be better predictors of word recall and reasoning performance, as compared to the self-report indicators of the demands of particular occupations.

DOT Job Complexity and Cognitive Performance

Table 26 shows the means, standard deviations, and skewness for the variables to be used in the models. The new DOT job complexity variables showed no problems with distributional normality. Again, the main sample was randomly divided into two sub-samples used to derive and replicate the models. Table 27 presents the demographic and self-rated health characteristics of the two sub-samples. A MANOVA comparing the demographic and self-rated mental health characteristics of the sub-samples revealed no significant differences (Wilks' λ=.999, $F(6, 4858)$= .763, p= .599), indicating the random selection produced groups that were demographically comparable.

The measurement model for the DOT indicators consisted mainly of single indicator latent variables. Each of the DOT complexity code factors was constructed by constraining the error variance of the factor to the indicator variance multiplied by the reliability of the measured indicator as reported by Cain and Treiman (1981). Because the measurement model was relatively simple in structure, an extensive cross-validation was not undertaken. The measurement model will be cross-validated when the replicability of the structural model is assessed. The final measurement

Table 26

Mean, Standard Deviations, and Skewness of the DOT

Job Complexity Model Variables

(N= 4865)

Variable	Mean	Standard Deviation	Skewness
Age	54.46	5.12	-.71
Gender	1.55	.50	-.19
Race	1.25	.43	1.15
Years of education	12.65	2.92	-.74
Occupation	2.75	1.33	-.09
CES-D	15.12	3.76	1.70
Mental health	2.40	.98	.24
Immediate word recall	7.89	2.56	.59
Delayed word recall	6.01	2.65	.72
Reasoning	6.42	2.95	-.01
Years experience	16.28	12.25	.46
DOT Data	3.05	1.97	.40
DOT People	5.72	2.11	-1.05
DOT Things	4.70	2.44	-.35

Table 27

Demographic Characteristics of the Two Subsamples used to Devise and Replicate the DOT Job Complexity Models

Variable		Sample 1 N= 2433	Sample 2 N= 2432
Age	M	54.48	54.45
	SD	5.12	5.12
Gender[a]	M	1.54	1.55
	SD	.50	.50
Race[b]	M	1.25	1.25
	SD	.43	.43
Years of Education	M	12.71	12.60
	SD	2.87	2.97
Self-reported Mental Health[c]	M	2.39	2.41
	SD	.97	1.00
Occupation[d]	M	2.76	2.74
	SD	1.33	1.33

[a] Gender: 1= Male, 2= Female
[b] Race: 1= Caucasian, 2= Non-Caucasian
[c] Self-reported mental health on a 5-point scale (1= excellent to 5 = poor).
[d] Rated on a 5-point scale (1= professional, 2 = semiprofessional, 3 = skilled, 4 = semiskilled, and 5 = unskilled).

model is presented in Table 28. As seen in the table, the model fit the data very well, and all variables had significant loadings on their respective factors. This model was therefore used as the basis for the more complex structural models that follow.

The base structural model for the DOT indicators is presented in Figure 3. Similar to the self-report indicators, the different aspects of occupational complexity were modeled as correlated disturbances. Further, the three forms of occupational complexity were modeled as having direct links to reasoning, but only affecting word recall indirectly. Finally, the paths from the control variables (not shown in Figure 3) were modeled as predictors of each of the individual factors. The initial structural model fit the data very well ($\chi^2(22)= 45.96$, $p = .002$, NFI= .994, CFI= .997). An inspection of the parameter estimates revealed that the path from DOT Things to Reasoning were not statistically significant ($z = .665$). This path was eliminated and the model was rerun. The new model also produced a good fit to the data ($\chi^2(23)= 46.40$, $p = .003$, NFI= .994, CFI= .997, $\Delta\chi^2(1)= .44$, $p > .05$). Inspection of the modification indices revealed that the addition of the path from DOT Data to Word Recall would improve the overall fit of the model. This path was added, and the resultant model produced a marginally better fit to the data ($\chi^2(22)= 42.79$, $p = .005$, NFI= .994, CFI= .997, $\Delta\chi^2(1)= 3.61$, $p < .10$). An inspection of the modification indices and residual covariances revealed no additional modifications were necessary.

Before the final structural model was interpreted, the replicability of the structural parameters was assessed. The final structural model was used as the basic model for both samples, and fit the data well ($\chi^2(44)= 120.44$, $p < .001$, NFI=

Table 28

Standardized Factor Loadings and Communalities for the DOT Occupational

Complexity, Mental Health and Cognition Model

$\chi^2(9) = 6.23$, $p = .716$, NFI = .999, CFI = 1.000.

Variable	Word Recall	Reasoning	Mental Health	DOT Data	DOT Things	DOT People	Communality
Immediate recall	.905						.819
Delayed recall	.864						.746
Similarities		.917					.841
Mental health			.845				.714
CES-D			.558				.311
DOT data				.922			.850
DOT things					.679		.461
DOT people						.933	.870

.992, CFI= .995). Next, both the measurement model and structural model parameters were constrained equal in both sub-samples. This model also fit the data well ($\chi^2(80)$= 164.88, p < .001, NFI= .989, CFI= .994, $\Delta\chi^2(36)$= 44.44, p>.05). Although constraining all parameters did not significantly degrade the overall fit of the model, modification indices revealed releasing one of the constraints would improve the fit of the model. Specifically, allowing the path between occupational experience and Reasoning to be freely estimated in both samples would decrease the chi-square by almost 10 units. The standardized path coefficient from occupational experience to Reasoning was .039 in sample 1, and -.037 in sample 2. Although the difference between the two estimates actually changed in sign, neither parameter was statistically reliable. Since the constraint did not involve any of the relationships among the DOT occupational complexity or cognitive factors, the difference between the coefficients were considered to be a relatively minor misspecification of the model.

The relationships among the demographic control variables and the DOT indicators of occupational complexity are presented in Table 29. The relationships to the DOT indicators will be the focus in the present context as the pattern of relationships of the cognitive factors are similar to those discussed already. For DOT Data, age, gender, race and Mental Health were positively related to the occupational rating. This indicated that individuals who were older, female, non-caucasians, and individuals who rated themselves in poorer mental health performed less complex job functions. Both education and occupational experience were negatively related to

Table 29

Standardized Parameter Coefficients for the Demographic Control Variables and the DOT Occupational Complexity Indicators, and Cognitive Factors

	Factor				
Demographic Variable	Memory	Reasoning	DOT Data	DOT People	DOT Things
Age	-.100	-.052	.045	-.001*	.094
Gender	.152	.115	.042	-.096	.083
Race	-.100	-.208	.124	.015*	.061
Education	.112	.397	-.409	-.373	.300
Occupational experience	.004*	.039*	-.115	-.087	-.194
Mental Health	-.029*	-.075	.100	.111	-.045*

All estimates are statistically significant except where indicated * $p > .05$.

DOT Data, indicating that more complex work activities were performed by individuals with higher levels of educational attainment, and individuals who had more years of occupational experience. For the DOT People code, Mental Health was again positively related to occupational complexity whereby individuals who reported poorer mental health occupied positions with relatively subservient interaction with individuals. Gender, education, and occupational experience were all negatively related to the DOT People code. This indicates that women, and people with higher education or more years of occupational experience, were more likely to occupy roles that were characterized as mentoring relationships with individuals they interact with at work. Finally, the DOT Things code was positively related to age, gender, race, and education. This indicated that older adults, women, non-caucasians, and individuals with more years of education occupied positions that required less complex interaction with things. Occupational experience, on the other hand, was negatively related to the DOT Things code.

Before turning to the structural relations among the factors, a discrepancy among the different DOT complexity codes must be addressed. Among the relationships with education, both the data and people code were negatively related to years of education, but the things code was positively related to amount of schooling. Remember that the DOT codes are organized such that more complex occupations are supposed to have lower DOT values. With such a scheme, one would expect negative relations with education for all of the DOT codes. It appears that the DOT Things code may not be organized in a manner that is easily interpreted as successive differences in complexity. Indeed, if one looks at the description of the DOT complexity codes (see Appendix B), it is clear that unlike the data and people codes, there is no consistent pattern of occupational complexity for the things code. In fact, the relationship to years of education actually suggests that this code may be inversely related to the other DOT measures. This inconsistency will prove important when interpreting the structural model among the DOT and cognitive factors.

The final DOT occupational complexity and cognition model, and parameter estimates, are presented in Figure 11. As seen in the figure, the data and people codes are positively related to each other, but negatively related to the things complexity code. This provides further evidence that the things code is inversely related to the complexity of the other occupation codes. Among the predictors of cognitive performance, the DOT data code was the strongest indicator, predicting roughly 1% to 1.5% of the variance in Reasoning, and slightly less variance in word recall performance. The DOT things code was positively related to Reasoning performance, predicting less than .5% of the variance in this measure, and this was statistically reliable in only sample 2.

An additional model was run using samples consisting of individuals with more or less than 1 year occupational experience. Again, this was done to test whether people who are new to an occupation, and are presumably still learning the various skills, would show a stronger relationship between occupational complexity and cognitive performance. The demographic characteristics of the samples with more or less than 1 year of occupational experience are presented in Table 30. A MANOVA

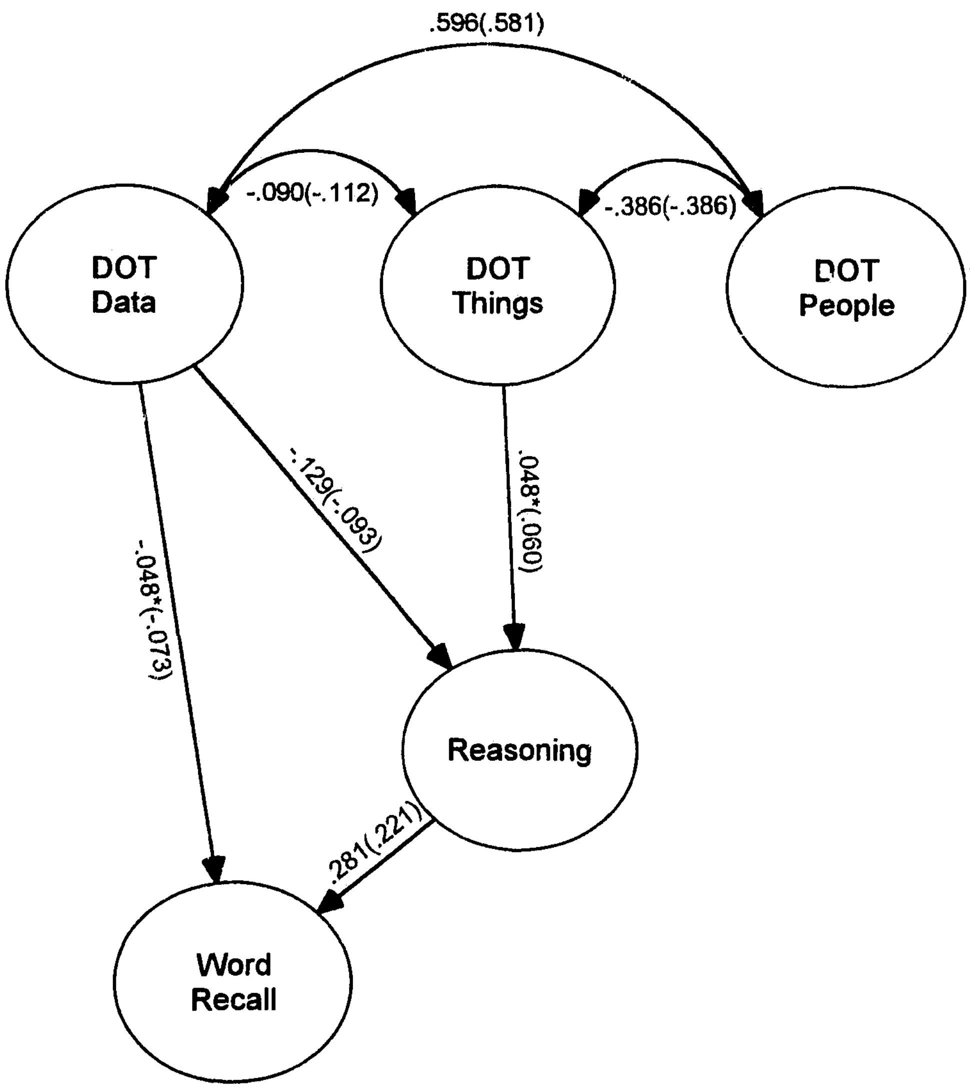

Figure 11
Final DOT Job Complexity and Cognition Model with Sample 1 and Sample 2 Estimates
(Sample 2 in parentheses)

(* p > .05)

Table 30

Demographic Characteristics of the DOT Occupational Complexity Sub-samples who were Currently Employed for Up to or More Than 1 Year

		Length of Employment	
		Up to 1 year	More than 1 year
Variable		N= 474	N = 4391
Age	M	53.41	54.58
	SD	5.95	5.01
Gender[a]	M	1.64	1.54
	SD	.48	.50
Race[b]	M	1.25	1.25
	SD	.43	.43
Years of Education	M	12.26	12.70
	SD	3.26	2.88
Self-reported Mental Health[c]	M	2.51	2.39
	SD	1.00	.98
Occupation[d]	M	3.22	2.70
	SD	1.21	1.33

[a] Gender: 1= Male, 2= Female
[b] Race: 1= Caucasian, 2= Non-Caucasian
[c] Self-reported mental health on a 5-point scale (1= excellent to 5 = poor).
[d] Rated on a 5-point scale (1= professional, 2 = semiprofessional, 3 = skilled, 4 = semiskilled, and 5 = unskilled).

indicated that both samples were not comparable demographically (Wilks $\lambda = .978$, $F(6, 4858) = 17.88$, $p < .001$). As seen in the table, people who were employed for 1 year or less tended to be younger ($F(1,4863) = 22.18$, $p < .001$), were more likely to be female ($F(1,4863) = 16.90$, $p < .001$), had fewer years of education ($F(1,4863) = 9.58$, $p = .002$), occupied less prestigious occupations ($F(1,4863) = 66.94$, $p < .001$), and rated their mental health as being slightly poorer ($F(1,4863) = 6.90$, $p = .009$). Although both samples were not comparable demographically because the structural analyses assess relationships independent of these confounding variables, differences among the DOT codes and cognitive performance resulting from demographic differences were not expected.

Again, the structural model testing the influence of occupational experience was the final model described earlier with one exception. Occupational experience was not used as a control variable in the analysis because the focus of the analysis was on differences due to occupational experience. The initial, unconstrained, model fit the data well ($\chi^2(40) = 122.05$, $p < .001$, NFI= .991, CFI= .994). Next, the measurement and structural model parameters were constrained to be equal across the two samples. This model produced a significant decrement in fit ($\chi^2(71) = 200.51$, $p < .001$, NFI= .986, CFI= .991, $\Delta\chi^2(31) = 78.46$, $p < .05$). Examination of the modification indices revealed that the main source of the ill-fitting model was 4 constrained parameters. Specifically, the paths (with standardized parameter estimates for the sample with more or fewer years of experience in parentheses) from gender (.145, -.052), race (.049, .150), and education (.275, .063) to DOT Things were not the same across the two samples. Further, the path from gender to DOT Data was positive (standardized estimate= .078) in the sample of individuals with greater than 1 year of experience, but was negative (-.129) in the sample with fewer years of occupational experience. Although some of the parameters were not equivalent across the two samples, the critical parameters dealing with the cognitive and job complexity latent variables were not statistically different across the two samples. Therefore, similar to the results from the models that used self-report indicators of occupational complexity, the current model provided very little evidence of increased predictive power of occupational complexity resulting from selecting individuals with fewer years of occupational experience.

The final model that tested the predictive power of the DOT occupation complexity indicators used a sample of unemployed individuals. This model was designed to test whether the relationship between occupational complexity and cognition is a legitimate one, or simply represents a spurious relationship based on education achievement or other unmeasured characteristics. It was expected that in the unemployed sample, the DOT complexity codes would fail to predict cognitive performance, since for individuals who are not currently employed, the complexity of the previous work environments should exhibit a weaker relationship with current cognitive functioning. The means, standard deviations, and skewness for the variables used in the models are presented in Table 31. The variables that were examined were the same as those used in the previous DOT occupational complexity models with two exceptions. First, the DOT complexity codes represent the

Table 31

Mean, Standard Deviations, and Skewness of the DOT

Job Complexity Model Variables for the Unemployed Sample

(N= 2050)

Variable	Mean	Standard Deviation	Skewness
Age	57.16	6.37	-.31
Gender	1.55	.50	-.22
Race	1.28	.45	.98
Years of education	11.66	3.16	-.77
CES-D	16.71	5.42	1.40
Mental health	2.71	1.17	.16
Immediate word recall	7.35	2.57	.53
Delayed word recall	5.47	2.51	.70
Reasoning	5.77	2.94	.06
Years since last employment	5.91	4.88	1.17
DOT Data	3.49	2.05	.05
DOT People	6.10	1.86	-1.17
DOT Things	4.57	2.43	-.25

occupational complexity of an individuals' previous work setting. Second, instead of measuring occupational experience, the number of years since the individual was employed in their previous occupation was assessed. It was expected that the number of years since the person was last gainfully employed may affect the relationship between occupational complexity and cognition.

The structural model that was tested was the final model for the sample who were currently employed. This model provided a good fit to the data for the unemployed sample ($\chi^2(22) = 48.88$, $p < .001$, NFI= .993, CFI= .996). Examination of the parameter estimates from the DOT job complexity factors to the cognitive factors revealed some interesting results. The path from DOT Things to Reasoning was no longer statistically reliable ($z = .659$). However, the paths from DOT Data to Word Recall, and Reasoning were still statistically reliable ($z = -2.26$, $z = -5.45$, respectively). This suggests that individual's previous work environment predicts their current cognitive functioning! The magnitudes of these significant relationships were consistent with those seen from the employed sample (standardized parameter coefficients= -.061, and -.142, respectively). Further, this relationship was observed independent of time since last employment, which was controlled statistically.

Summary

In general, there is evidence that some aspects of individuals' work environments predict significant amounts of variance in cognitive performance, as measured by performance on word recall and an abstract reasoning task. It appears that the types of demands, either physical or mental, that are placed upon an individual are not as important as the initiative that workers are allowed to display in deciding the types of work tasks they perform. Specifically, a factor indexing the extent to which an occupation allowed for freedom to decide how work was done predicted between 7% and 12% of the variance in Reasoning performance. On the other hand, specific work demands, indexed with self- and standardized-ratings, predicted substantially less variance in cognitive performance, up to 1% of variance in word recall and reasoning performance.

Although the results were suggestive of a relationship between occupational complexity and cognitive performance, additional results argued that caution should be taken when interpreting these relationships. Not only were measures of occupational complexity predictive of cognitive performance in an employed sample, but they also predicted approximately 2% of variance in reasoning performance in an unemployed sample. This might suggest that additional, unmeasured, variables are contributing to the relationship between occupational complexity and cognition.

Chapter VI

DISCUSSION

The present study examined the relationship between physical health, occupational complexity, and cognitive performance. This final chapter discusses the results and their implications. This chapter is organized such that the self-rated, cardiovascular disease, and objectively measured health status results will be presented first. Next, results from the analysis of occupational complexity, including self-report and standardized indices, will be summarized. Finally, limitations of the research and directions for future research are reviewed.

Physical Health and Cognitive Performance

The first research question dealt with the prediction of cognitive performance by self-report indicators of physical health. In addition to the role of health status in predicting performance, the structure of the health concept itself was also examined. Results indicated that self-reported physical health could be represented by five distinct factors corresponding to current and retrospective ratings of health status, as well as current ratings of the number of illness episodes, problems with activities of daily living, and incidence of chronic disease. Further, the relationships among these factors could be modeled such that chronic illness predicted illness episodes, ADL, and self-ratings of current health. Both illness episodes and ADL predicted current health. Finally, retrospective assessments of health status showed very little power in predicting current health status (only one parameter was statistically reliable, to ADL in sample 1).

The structure of the physical health factors was generally consistent with that reported by Liang (1986). There were a number of discrepancies between the current study and his results, however. First, in the current study the subjective health factor was identified differently. In Liang's study four self-ratings of health status were used, including: Ratings of (a) current health, (b) health compared to people their own age, (c) health compared to individuals 60 years of age, and (d) health from one year ago. In the current study, the question that asked for a rating of health from one year ago was not used to dimensionalize the subjective health factor. This reflected the fact that loading of this variable on the factor was unacceptably low (standardized loading = .254). In Liang's study, the standardized loading of this variable ranged from .338 to .487 in the four samples used to derive and cross-validate the measurement models. The most likely reason for the discrepancy are the additional variables that Liang used to measure subjective health. With the inclusion of variables requiring subjects to compare their current health status to that of other individuals their own age, as well as when they were 60 years-old, the subjective health factor that Liang observed may have been a more general factor than one that simply indexes a subject's current perceived health status.

The second difference from Liang's (1986) results was the absence of the path, in the present study, from illness episodes to current health. This indicated that the number of visits to a doctor, or the number of days sick in bed did not predict individuals' ratings of current health status. In Liang's (1986) study the standardized path coefficient between these two variables ranged from -.096 to -.173, indicating that between 1% and 3% of variance in current health could be predicted by number of illness episodes. This discrepancy between the two studies may reflect differences in the identification of subjective health status, or may result from the differences in sample composition between the two studies. In Liang's study the participants ranged in age from 65 years and older, whereas in the current study, the majority of individuals were under 62 years of age. Using an older sample could have increased the incidence of health-related impairment that was observed. Remember, variables indexing illness episodes showed problems with distributional normality. As such, the variance of these indicators may have been truncated in relation to that observed with Liangs' (1986) sample of older adults, and this could have resulted in a weakened relationship between illness episodes and current health.

Finally, the parameter estimates between the self-reported health factors obtained by Liang were consistently larger in magnitude than the ones seen in the present study. This difference could reflect differences in sample composition discussed already. On the other hand, the differences may reflect the fact that the parameters in the present study were independent of the influence of age, gender, race, education, and mental health, which were all controlled statistically. It may be the case that the parameter estimates observed by Liang (1986) were inflated by a relationship with some variable other than health. For example, the age-related variance that each health factor shares in common could act to increase the size of the relationships among the health factors themselves. Although there were several differences between the results of Liang (1986) and those in the current study, the identification of, and prediction by the self-report health status indicators were similar across the two studies.

Turning to the cognitive measures, several interesting results emerged. Results indicated that both current health ratings and incidence of chronic illness predicted significant amounts of variance in reasoning performance, approximately 1% in both cases. However, for current health, better self-rated health predicted higher reasoning scores, but for chronic illness, greater impairment predicted improved performance on the word similarities measure.

The prediction of significant portions of variance in word similarities by self-rated current health is consistent with a number of other investigations (e.g., Hultsch et al., 1993; Perlmutter & Nyquist, 1990). However, in terms of amount of variance in cognitive performance that is predicted by differences in health status, the current results may be of little practical importance. One goal of the present study was to examine the health/cognition relationship is a relatively diverse sample. Presumably, the diversity in health conditions that is afforded by a population-representative sample might increase the variance of health ailments, and in turn, could result in larger relationships between health status and cognitive performance. However, the results of the present study provide no evidence that the strength of the relationship between health and cognitive performance was increased in this representative sample of adults.

There are several potential reasons why the relationship between health status and cognitive performance was not larger in the current sample. First, perhaps the sample was not any more diverse in terms of amount of health problems as compared to other samples that have been utilized. In the current study, the range of ages that were examined were substantially lower than those typically examined. For example, the average age in the present study was approximately 55 years, but the average age in Hultsch et al. (1993) was roughly 70 years, and Perlmutter and Nyquist studied individuals who were in their eighties. Because the incidence of health impairment is positively correlated with age, it may be the older, volunteer samples that have the greater diversity in health status, relative to this younger population representative sample. Although this remains a possibility, there was little evidence for this argument from the cardiovascular disease model that utilized individuals over 61 years of age.

An additional factor that may have influenced the relationship between cognitive performance and health status was the types of cognitive tasks that were used. Perlmutter (1988) has argued that health status should be predictive of fluid cognitive abilities rather than more crystallized abilities. In the current study, cognitive performance was indexed by word recall and word similarities. It was thought that the word similarities would provide a more fluid indicator of cognitive performance than word recall, but this may not have been the case. Evidence for the crystallized demands of the word similarities measure comes from intercorrelations with other WAIS-R subtests. Weschler (1981) reports correlations of .51, and .46 between word similarities and the fluid indicators block design and digit symbol, respectively. On the other hand, the subtests that can be characterized as accessing crystallized abilities, vocabulary and information, correlate .72 and .66 with the word similarities measure, respectively. Therefore, the measure that was used to index fluid abilities may actually be more closely associated with crystallized abilities, and this may have resulted in an attenuated relationship between cognitive performance and health status. Therefore, the results are theoretically consistent with the predictions of Perlmutter (1988).

A final factor that deserves consideration is that in healthy adults samples there is no relationship between cognitive performance and physical health. It may be the case that a sufficient amount of health-related pathology is necessary to influence cognitive functioning. For example, Birren's (1959) discontinuity hypothesis suggests that different threshold values exist and after a boundary level is surpassed, sudden shifts in behavior may be evident. Perhaps there is a threshold of health-related pathology that the majority of the current sample has not surpassed and this resulted in a lack of a predictive relationship between health and cognitive performance. However, without the inclusion of fluid indicators of cognitive performance, no definitive conclusions can be made about the reason(s) why physical health did not predict substantial amounts of variance in cognitive performance in the present study.

The second significant path between the self-reported health factors and cognitive measures was a small positive relationship between chronic illness and reasoning. This indicated that individuals who reported a greater incidence of chronic disease tended to perform better on the word similarities measures when compared to individuals who reported fewer illnesses. Although the magnitude of this relationship was relatively small, approximately 1% of the variance in reasoning, it was just as large as the relationship with current health. Further, the path between chronic illness and reasoning was consistently observed in all models that included self-report indicators of physical health attesting to the generalizability of this finding. It is unclear what the paradoxical relationship between chronic illness and cognitive performance indicates.

Turning to the results of the cardiovascular disease analyses, the separation of CVD from chronic illness resulted in two well-defined factors representing blood pressure and heart disease. The new CVD factors exhibited significant predictive relationships with illness episodes, ADL, and current health. Further they were significantly correlated with chronic illness, and blood pressure was a significant predictor of heart disease.

Among the predictors of cognitive performance, both the chronic illness and blood pressure factors predicted significant amounts of variance in reasoning performance, approximately .3% of variance in both cases. Note that overall self-ratings of health status were no longer a reliable predictor of cognitive performance after the influence of the cardiovascular disease factors were added. This is consistent with results reported by Earles and Salthouse (1995). They found that the relationship between physical health and cognitive performance could be modeled through a cardiovascular disease factor, and that direct paths from overall self-ratings of physical health to cognitive performance were not required. The same results were observed in the present study. Once the path from the blood pressure factor to reasoning was added, the direct path from current health to reasoning was no longer statistically reliable. In terms of amount of variance accounted for, the results from the present study are not consistent with Earles and Salthouse (1995). They found that a CVD factor predicted between 5% and 30% of variance in sensory-motor speed, and between 5% and 25% in reaction time. These values are substantially greater than the variance that is accounted for in the present study, although the differences are likely due to the types of cognitive tasks that were used as outcome measures.

For the blood pressure factor, results indicated that presence of high blood pressure or medication to treat high blood pressure was associated with poorer reasoning performance. However, the amount of variance in reasoning that is accounted for by differences in blood pressure status may be of little practical importance. These results are consistent with a number of studies that have demonstrated little relation between high blood pressure and decrements in cognitive performance. For example, Farmer et al. (1987) found that neither blood pressure nor antihypertensive medication was significantly associated with performance on the word similarities test in a sample of 2,032 individuals aged 55-89 years. Similarly, Hertzog et al. (1978) found that hypertensives performed poorer on measures of psychomotor speed only, and actually increased in performance on several other cognitive measures, including spatial ability, numeric ability and IQ.

Additionally, it may be the case that the relatively low relationship between blood pressure and cognitive performance reflects how the blood pressure factor was identified. Because the blood pressure factor was identified with a measure that inquired about medication for high blood pressure this could have resulted in an attenuated relationship with cognitive performance. For example, Speith (1965) noted that the effect of high blood pressure on cognitive performance was only evident for individuals who were not taking prescribed medication. Because taking medication for high blood pressure was used to identify the blood pressure factor in the current study, this may have resulted in an attenuated relationship with cognitive performance.

The lack of a relationship between word recall or reasoning and heart disease is inconsistent with previous research. Both, Barrett and Watkins (1986) and Hertzog et al. (1978) demonstrated reliable decrements in cognitive performance that were attributable to self-ratings (Barret & Watkins, 1986) or medically defined (Hertzog et al., 1978) incidence of heart disease. However, in the case of Barret and Watkins (1986) only words that were unfamiliar to older adults produced significant differences between adults who reported cardiovascular illness, whereas there were no reliable differences for familiar words attributable to presence of cardiovascular disease. The differences between the current results and those obtained by Hertzog et al. (1978) could be attributed to how cardiovascular disease was identified. The participants from Hertzog et al.'s study were recruited from a health care maintenance organization. As such, information regarding the presence of cardiovascular disease was based on medical records for each individual. In the present case, information was obtained by self-ratings of the presence of heart attacks, heart surgery, or ratings of whether individuals had sought a physician's attention for heart problems. It is possible that the differences in how heart disease was measured could have lead to the lack of findings in the present case. On the other hand, the lack of significant findings may also relate to the types of cognitive outcome measures that were used, a possibility that was entertained for the lack of results with overall self-ratings of health status. In sum, although there was evidence that a small portion of variance in reasoning performance was attributable to differences in blood pressure, in general, there is very little evidence to suggest that cognitive performance was greatly affected by cardiovascular illness.

Focusing on the objective indices of physical health, vital capacity and grip strength showed little association between both the self-rated measures of physical health, blood pressure and chronic illness, as well as exhibiting little predictive power of word recall and reasoning. Therefore, it is not simply the case that the self-report measures failed to adequately dimensionalize the health concept, as the objective indices of physical health also failed to demonstrated a reliable relationship to cognitive performance. Again, the lack of a significant predictive relationship may reflect difficulties with the sample, cognitive outcome variables, or both.

In sum, there is very little evidence of substantial differences in cognitive performance that result from individual differences in self-reported or objective indices of physical health. As mentioned earlier, there are several potential reasons why significant relationships were not observed between the health and cognitive variables. First, the variance of the sample may have been truncated because of the overwhelming majority of the sample being in the age range of 51 to 61 years. On the other hand, the analysis that selected individuals 62 years of age and older, thereby possibly increasing the incidence of health impairment, did not show greater relationships between cognitive performance and self-reported health. The second possibility deals with the types of cognitive measures that were employed. Had more fluid indicators of cognitive performance been used, the relationships with self-reported and objective indices of physical health may have increased substantially.

Occupational Complexity and Cognitive Performance

The results using self-ratings of occupational demand indicated that four well-defined factors could represent occupational conditions associated with physical demand, mental demand, need to analyze data, and the latitude individuals are afforded to decide how their job is accomplished. Among the predictors of cognitive performance, both the Data and Freedom factors predicted significant portions of variance in cognitive performance. Specifically, the need to analyze data was positively related to performance on word recall, accounting for approximately .4% of the variance in this factor. Similarly, the Freedom factor was negatively related to word similarities indicating that individuals who were in occupations that afforded little freedom to decide how work was done performed poorer on the abstract reasoning measure. The path between these two variables was fairly strong, indicating that between 7% and 12% of the variance in reasoning could be accounted for by the freedom factor. Results indicated that there was no relationship between the physical or mental demands of the workplace and cognitive performance.

Therefore, it appears that the critical component of a workplace in predicting cognitive performance are not the specific tasks that are performed, but rather it is the freedom with which individuals are allowed to decide how these tasks are performed.

Results of this analysis are consistent with the findings of Kohn and Schooler (1973, 1978). They observed that the extent to which a person could use initiative, thought and independent judgment at work was related to an individual's intellectual flexibility. In the current study, this relationship was confirmed with a more standard measure of cognitive performance, abstract reasoning. It is interesting to note that occupational freedom affected only reasoning directly, as no direct path to word recall was necessary. Perhaps the types of demands that are present in the working environment correspond to the intellectual abilities best measured by the word similarities measure, rather than word recall.

The results of the study are also consistent with our previous analysis of this data (Small & Hultsch, 1993). However, in terms of amount of variance accounted for, the estimates obtained in the current study are far greater than those observed previously. For example, Small and Hultsch (1993) observed that between 1% and 2% of variance in reasoning could be accounted for by differences in occupational complexity, whereas in the present study, occupational complexity accounted for between 7% and 12% of performance. The reason for the increase in predictive power of the occupational complexity measures likely lies in the type of statistical methods that were employed to examine these relationships. In our previous analyses (Small & Hultsch, 1993), hierarchical multiple regression was used as the predominant means to analyze the relationships. In the current study, the data were analyzed with structural equation modeling techniques. SEM allows for the variance in a measure to be partitioned into its' relevant and error components. The separation of variance due to error, and variance due to meaningful effects may have resulted in a strengthening of predictive relationship between occupational complexity and word recall. Remember that Hertzog (1987) argues, "In cases where the communalities (variance in observed variables predicted by latent variables) are only moderate, the *disattenuated correlations* among factors can be considerably higher than the correlations among any pair of observed variables" (p. 267). In the case of the occupational complexity factor Freedom, the loadings of the measured variables on this factor were relatively moderate in size (.456 for repetitious nature of work, and -.346 for extent to which job afforded freedom). Instead of the relatively low loadings hindering the analysis of occupational complexity and cognitive performance, they may have provided a more accurate estimate of the extent to which an job does provide occupational freedom, resulting in an increase in the predictive power of this factor. In sum, the use of SEM in the present case resulted in an increase in the predictive relationship between occupational complexity and cognitive performance, attesting to the usefulness of this analytic procedure.

The results of the analysis comparing individuals with more or less relevant work experience provided no evidence for a greater relationship between occupational complexity and cognitive performance as a function of occupational experience. This contrasts with expectations derived from Murphy's (1989) characterization of an occupations' transition and maintenance phases. It was expected that individuals with one year or less occupational experience would exhibit a stronger relationship between occupational complexity and cognitive performance because they would be in a transition stage in which new job tasks and functions are being learned. In the current study, there was no difference in the magnitude of the relationships between occupational complexity and cognitive performance for individuals with more or less relevant occupational experience.

There are several potential explanations for the lack of differences in parameter estimates for individuals with more or less occupational experience. First, the length of time used to classify individuals in the present study may have been too broad. Murphy (1989) notes that the transition stage may only last for a period of 3 to 6 months. Unfortunately, in the present study, too few individuals were employed for less than one year to allow for this type of fine grained analysis. Second, using time employed to classify individuals may not fully represent the types of demands that individuals are exposed to. For example, differences in prior skill level, as well as proficiency of work could act to influence the relationship between occupational complexity and cognitive performance. A better method to evaluate the relationship between occupational complexity, occupational experience, and cognitive performance, would be to examine individuals performance longitudinally.

The results of the analyses using the Dictionary of Occupational Titles job complexity measures indicated that little variance in reasoning or word recall was predicted by these measures. These results are consistent with those observed with self-report indicators suggesting that the types of demands, physical or mental, are not as important in predicting cognitive performance as the freedom an occupation affords the employee to decide how the tasks are accomplished. The results using the DOT job complexity indicators were also consistent with the results from the self-report indicators regarding the influence of occupational experience and the predictive power of occupational complexity. Results indicated that the effects of job complexity were virtually identical for individuals who had more, or less, than one year of experience on the job.

Although the results from the DOT job complexity analyses were generally consistent with those from the self-report indicators, one set of DOT analyses provided some potentially troubling results. Specifically, the analysis of unemployed individuals indicated that a predictive relationship between the DOT indicators and word recall and reasoning still existed for individuals in this sample. This finding raises the troubling possibility that the results between occupational complexity and cognition represent a spurious correlation based upon educational selection, or some other similar effects. One might expect that a job a person occupied previously would produce a weakened relationship between occupational complexity and cognitive performance.

However, there are several reasons why the relationship between occupation complexity and cognitive performance likely represents a real, rather than spurious, relationship. First, the possibility of an educational selection effect was minimized by controlling the educational attainment of the participants by statistical means. Second, one might expect a less differentiated relationship between occupational complexity and cognitive performance than seen in the current study. Only some of the self-rated and DOT job complexity measures were predictive of reasoning. If the relationship to cognitive performance was due to educational attainment, or similar variable, one might expect that all aspects of an occupation that are related to education should be predictive of cognitive performance. For example, turning to the relationships between education and the occupational complexity factors, each factor was significantly related to an individuals level of educational attainment. The path to the freedom factor was the largest (standardized parameter coefficient = -.403), but was followed closely by paths to the data (.380), physical demand (-.350), and mental demand (.264) factors. Therefore, it is clearly not the case that all factors that are related to education are predictive of cognitive performance.

The relationship between DOT job complexity and cognitive performance that was observed in the unemployed sample may also be related to how environmental complexity is thought to influence cognitive performance. Schooler (1989) has argued that the method through which the demands of an occupation affects individual functioning is through a process called "cognitive generalization." Specifically, individuals who enjoy occupations that allow for a great deal of freedom regarding decisions how work is done are more likely to seek complex environments as compared to individuals who work in structured environments. For example, Miller and Kohn (1983) reported that individuals who work in relatively complex environments also seek intellectually demanding leisure time activities. It may be the case that individuals who were unemployed, but previously held complex occupations, may still be motivated to seek out other complex environments and this results in the relationship between previous occupation and current level of cognitive functioning.

Similarly, the relationship between previous occupational complexity an current cognitive functioning might reflect some sort of "carry-over" effect. Willis and Nesselroade (1990) noted that individuals who received training on a figural relations task showed higher performance, as compared to baseline ability, up to 5 years after a training program was first administered. Specifically, 64% of the training group's performance was consistently above baseline, compared with 33% of the control group's. Therefore, considering the results from Willis and Nesselroade (1990), it may be possible that an occupation that was held previously could influence an individuals current level of cognitive functioning.

In sum, there is evidence suggesting that occupations in which individuals are allowed to make decisions about how work is performed are related to better performance on some tests of cognition. However, evidence from standardized indicators of job complexity in an unemployed sample suggest that this relationship could be indexing an effect other than the influence of occupational complexity on cognitive performance. In this next section, several potential means to investigate the relationship between occupational complexity and cognitive performance are offered. In addition, other limitations of the present study are discussed.

Limitations and Directions for Further Research

In this next section, several limitations of the present study, and means to overcome these limitations in future studies are offered. The first three limitations deal with methodological changes that could be made to better understand the relationship between physical health, occupational complexity and cognitive performance. The final two limitations deal with more substantive issues related to the questions at hand.

The use of an extant data set, such as the Health and Retirement Survey, is not without its disadvantages. Although the current data set allowed the relationship between physical health, occupational complexity, and cognitive performance to be examined in a very large, population representative sample, there are several aspects of the data that could be improved upon. First, because the incidence of health-related disorders increase with age, the upper end of the age spectrum could have been better represented. With a more diverse set of age groups, the distributional problems of the health measures that were encountered during model development may have been lessened. It would not be expected that all of the health variables would be distributed normally in a data set with older individuals. For example, one would not expect incidence of heart disease to be normally distributed because this ailment does not occur widely in the population. However, a better representation of ages may have produced more diversity in the level of health-related impairment that was encountered.

A second limitation deals with the types of measures that were not included in the study. Most notably, the absence of multiple domains of cognitive functioning being assessed. One explanation why the physical health variables failed to account for substantial portions of variance in cognitive performance was the absence of measures of fluid abilities. With the inclusion of speed-related or inductive reasoning measures, the relationship to physical health would have likely increased in magnitude. The inclusion of multiple domains of cognitive functioning could also be informative regarding the relationship with occupational complexity. For example, in the present study, occupational complexity was more predictive of reasoning than word recall. With the inclusion of additional cognitive measures more comparisons among the predictive relationships with occupational complexity could be made. Among the measures of physical health and occupational complexity, both domains were fairly well-represented in the current study. Of course, modifications to the health measures can be made, such as the inclusion of more medically based (e.g., blood pressure, physician reports of illness) indicators of physical health, but in general the health concept was well identified.

Further, no information was gathered about the complexity of an individuals previous occupation. In light of the evidence indicating that prior job complexity predicts current cognitive functioning in the sample of unemployed adults, assessing the predictive power of the complexity of the previous occupation on current cognitive functioning would have been informative. For example, Kohn and Schooler (1973) demonstrated that the substantive complexity of an individual's prior occupation predicted the complexity of an individual's current occupation, but not their current intellectual flexibility. Had the complexity of the previous occupation been assessed in the current study, similar predictive relationships could have been examined.

The third limitation is also one that deals with measures that were not included, but in this case, it is the use of multiple indicators of performance. In some of the structural equation models, single indicator latent variables were used. Although this is not problematic when estimates of reliability are available (e.g., word similarities) and is actually advocated by some (Anderson & Gerbing, 1988), this issue becomes more controversial when no evidence for measure reliability exists. The inclusion of multiple indicators for each domain would have allowed for well-defined factors, without the problems associated with constraining the variance of an indicator to an estimate that may be unreasonable.

The final two limitations deal with more substantive issues regarding the relationship between physical health, occupational complexity, and cognitive performance. The first limitation deals with the problem of education selection effects in research that examines the influence of environmental complexity on cognitive performance. Next, the focus of studies should change from those that simply describe the relationship between physical health or occupational complexity and cognitive performance, to ones that attempt to elucidate the means of these influences on cognitive performance.

The potential for the educational attainment, or other related abilities, of a study participant to influence the relationship between occupational complexity and cognitive performance is a confound that all researchers who attempt to study these relationships must address. In the current study the influence of education was controlled by statistical means. However, there are additional means by which this influence can be addressed. For example, in addition to examining the relationship between occupational complexity and cognitive performance cross-sectionally, Kohn and Schooler (1978) examined a subset of participants longitudinally. With longitudinal data, the problem of an education selection effect is no longer present. as the change in individuals occupational complexity can be examined in relation to changes in cognitive performance. The results of Kohn and Schooler's (1978) study indicated that substantively complex occupations affected individuals' intellectual flexibility longitudinally.

An additional means to examine the relationship between occupational complexity and cognitive performance may be to focus on a single occupation. A study could be designed in which individuals in an occupation with similar educational demands, but vary in terms of amount of freedom with which people decide how work is accomplished, could be compared on a variety of measures of cognitive ability. Presumably, if occupational freedom is the source of the relationship with cognitive performance, then individuals who vary on this factor, but not on all others, would perform better cognitively.

The final limitation deals with a change from the description of the phenomenon, to an explanation of how physical health or occupational complexity exerts an influence on cognitive functioning. For example, Schooler (1989) offered a glimpse of the mechanism by which environmental complexity affects cognitive performance in his cognitive generalization hypothesis. Schooler argues that the influence of environmental complexity is mediated by self-directedness of orientation. Self-directedness appears to be related to the motivation of an individual. Schooler (1989) suggested that, "The effect of self-directed work among employed workers also seems to be in large part indirect - self-directed work leading to a self-directed orientation, which in turn leads to intellectual flexibility" (p. 141). Thus, studies that examine the relationship between environmental complexity and cognitive performance should also included measures related to the motivation, or self-directedness of the research participants. With the inclusion of additional variables, such as self-directedness, we may be better able to predict who, and in what occupational settings, would be expected to exhibit a beneficial relationship between occupational complexity and cognitive performance.

Summary

In sum, the present study contributes to our understanding of the relationship between physical health, occupational complexity and cognitive performance. Very little evidence was found for a large relationship between differences in physical health being predictive of differences in cognitive functioning. This was true for both objective and subjective indices of physical health. However, this relationship may have been masked by the use of more crystallized measures of cognitive performance. With respect to occupational complexity, the freedom with which individuals are allowed to decide how their work is accomplished was related to better performance on the word similarities test. There was little predictive relationship between the specific types of demands that individuals experience in the workplace. This suggests that it is not what is done, but how it is done that affects cognitive performance. The results also suggested that caution must be taken when interpreting these relationships because of the potential for differences due to educational attainment to influence the relationship between occupational complexity and cognitive performance.

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Appendix A: Words used as Items in Immediate and Delayed Word Recall

lake	car
army	forest
ticket	city
cabin	door
mountain	pipe
plant	bird
corn	iron
coffee	steam
cat	winter
ship	dust

Appendix B: Dictionary of Occupational Titles Job Complexity Code

Much of the information in the Dictionary of Occupational Titles (Department of Labor, 1977) is based on the premise that every job requires a worker to function in some degree to Data, People, and Things. These relationships are identified and explained below. They appear in the form of three listing arranged in each instance from the relatively simple to the complex in such a manner that each successive relationship includes those that are simpler and excludes the more complex. The identifications attached to these relationships are referred to as worker functions, and provide standard terminology for use in summarizing exactly what a worker does on the job.

A job's relationship to Data, People, and Things can be expressed in terms of the lowest numbered function in each sequence. These digits express a job's relationship to Data, People, and Things by identifying the highest appropriate function in each listing as reflected by the following table:

DATA	**PEOPLE**	**THINGS**
0 Synthesizing	0 Mentoring	0 Setting-Up
1 Coordinating	1 Negotiating	1 Precision Working
2 Analyzing	2 Instructing	2 Operating-Controlling
3 Compiling	3 Supervising	3 Driving-Operating
4 Computing	4 Diverting	4 Manipulating
5 Copying	5 Persuading	5 Tending
6 Comparing	6 Speaking-Signalling	6 Feeding-Offbearing
	7 Serving	7 Handling
	8 Taking Instructions-Helping	

Definitions of Worker Functions

DATA: Information, knowledge, and conceptions, related to data, people, or things, obtained by observation, investigation, interpretation, visualization, and mental creation. Data are intangible and include numbers, words, symbols, ideas, concepts, and oral verbalization.

0 Synthesizing: Integrating analyses of data to discover facts and/or develop knowledge concepts or interpretations.

1 Coordinating: Determining time, place, and sequence of operations or action to be taken on the basis of analysis of data; executing determination and/or reporting on events.

2 Analyzing: Examining and evaluating data. Presenting alternative actions in relation to the evaluation is frequently involved.

3 Compiling: Gathering, collating, or classifying information about data, people or things. Reporting and/or carrying out a prescribed action in relation to the information is frequently involved.

4 Computing: Performing arithmetic operations and reporting on and/or carrying out a prescribed action in relation to them. Does not include counting.

5 Copying: Transcribing, entering, or posting data.

6 Comparing: Judging the readily observable functional, structural, or compositional characteristics (whether similar to or divergent from obvious standards) of data, people, or things.

PEOPLE: Human beings; also animals dealt with on an individual basis as if they were human.

0 Mentoring: Dealing with individuals in terms of their total personality in order to advise, counsel, and/or guide them with regard to problems that may be resolved by legal, scientific, clinical, spiritual, and/or other professional principles.

1 Negotiating: Exchanging ideas, information, and opinions with others to formulate policies and programs and/or arrived jointly at decisions, conclusions, or solutions.

2 Instructing: Teaching subject matter to others, or training others (including animals) through explanation, demonstration, and supervised practice; or making recommendations on the basis of technical disciplines.

3 Supervising: Determining or interpreting work procedures for a group of workers, assigning specific duties to them, maintaining harmonious relations among them, and promoting efficiency. A variety of responsibilities is involved in this function.

4 Diverting: Amusing others. (Usually accomplished through the medium of stage, screen, television, or radio.)

5 Persuading: Influencing others in favor of a product, service, or point of view.

6 Speaking-Signalling: Talking with and/or signalling people to convey or exchange information. Includes giving assignments and/or directions to helpers or assistants.

7 Serving: Attending to the needs or requests of people or animals or the expressed or implicit wishes of people. Immediate response is involved.

8 Taking Instructions-Helping: Helping applies to "non-learning" helpers. No variety of responsibility is involved in this function.

THINGS: Inanimate objects as distinguished from human beings, substances or materials; machines, tools, equipment and products. A thing is tangible and has shape, form, and other physical characteristics.

0 Setting up: Adjusting machines or equipment by replacing or altering tools, jigs, fixtures, and attachments to prepare them to perform their functions, change their performance, or restore their proper functioning if they break down. Workers who set up one or a number of machines for other workers or who set up and personally operate a variety of machines are included here.

1 Precision Working: Using body members and/or tools or work aids to work, move, guide, or place objects or materials in situations where ultimate responsibility for the attainment of standards occurs and selection of appropriate tools, objects, or materials, and the adjustment of the tool to the tasks require exercise of considerable judgment.

2 Operating-Controlling: Starting, stopping, controlling, and adjusting the progress of machines or equipment. Operating machines involves setting up and adjusting the machine or material(s) as the work progresses. Controlling involves observing gages, dials, etc., and turning valves and other devices to regulate factors such as

temperature, pressure, flow of liquids, speed of pumps, and reactions of materials.

3 Driving-Operating: Starting, stopping, controlling the actions of machines or equipment for which a course must be steered, or which must be guided, in order to fabricate, process, and/or move things or people. Involves such activities as observing gages and dials; estimating distances and determining speed and direction of other objects; turning cranks and wheels; pushing or pulling gear lifts or levers. Includes such machines as cranes, conveyor systems, tractors, furnace charging machines, paving machines, and hoisting machines. Excludes manually powered machines, such as handtrucks and dollies, and power assisted machines, such as electric wheelbarrows and handtrucks.

4 Manipulating: Using body members, tools, or special devices to work, move, guide, or place objects or materials. Involves some latitude for judgment with regard to precision attained and selecting appropriate tool, object, or material, although this is readily manifest.

5 Tending: Starting, stopping, and observing the functioning of machines and equipment. Involves adjusting materials or controls of the machine, such as changing guides, adjusting timers and temperature gages. Turning valves to allow flow of materials, and flipping switches in response to lights. Little judgment is involved in making these adjustments.

6 Feeding-Offbearing: Inserting, throwing, dumping, or placing materials in or removing them from machines or equipment which are automatic or tended to operated by other workers.

7 Handling: Using body members, handtools, and/or special devices to work, move or carry objects or materials. Involves little or no latitude to judgment with regard to attainment of standards or in selecting appropriate tool, object, or material.

VITA

Surname:	Small	Given Names:	Brent John
Place of Birth:	Toronto, Ontario	Date of Birth:	2 July 1965

Educational Institutions Attended:

University of Victoria	1988-1995
University of Toronto	1984-1988

Degrees Awarded:

M.A. (Psychology)	University of Victoria	1992
B.Sc. (Biology/Psychology)	University of Toronto	1988

Publications:

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