ABSTRACT

Individual Differences as Predictors of Accidents in Early Adulthood

J. Kenneth Young, Ph.D.

Mentor: A. Alexander Beaujean, Ph.D.

Within the last decade, researchers within the field of epidemiology have begun to use measures of intelligence to predict health-related outcomes in the emerging sub-field of cognitive epidemiology (CE). Researchers within CE have been successful in demonstrating that intelligence is a significant predictor of important heath-related outcomes ranging from mortality to dementia (Batty, Deary, & Gottfredson, 2007; Snowdon, et al., 1996), often independent of potentially confounding variables (e.g., socioeconomic status). One health outcome that has not been thoroughly explored in the CE literature is accidents and unintentional injuries. Such health impairments pose a significant health threat for adults and children, due to their long term sequelae, both individually (Berger & Mohan, 1996), and at the public health level (Segui-Gomez & Mackenzie, 2003). Subsequently, their investigation and, ultimately, prevention appears to be a fruitful area of inquiry. One potentially confounding variable that has not been investigated extensively in the study of accidents, as well as CE literature in general is personality--despite a literature that suggests certain personality measures predict important life outcomes (Roberts, et al., 2007).

The current study used probit regression with unobserved latent variables to investigate the relationship between cognitive ability (as measured during early adolescence) and personality traits in predicting accident incidence in early adulthood using the National Longitudinal Study of Adolescent Health dataset. Childhood socioeconomic status and adulthood physical activities were used as covariates. Findings suggest that neither childhood IQ nor personality proved to be meaningful predictors of accidents in early adulthood, but physical activity in adulthood was a consistent and meaningful predictor. Discussion, limitations, and suggestions for future research conclude the study.

Individual Differences as Predictors of Accidents in Early Adulthood

by

J. Kenneth Young, B.S., M.Div.

A Dissertation

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Eric L. Robinson, Ph.D., Interim Chairperson

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Approved by the Dissertation Committee

____

A. Alexander Beaujean, Ph.D., Chairperson

____

Eric L. Robinson, Ph.D.

____

Terrill F. Saxon, Ph.D.

____

Rodney G. Bowden, Ph.D.

____

Rafer S. Lutz, Ph.D.

Accepted by the Graduate School
December 2008

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J. Larry Lyon, Ph.D., Dean

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As I sit to write this, many churches around the world are celebrating the lives of the faithful for All Saints Day. They are telling stories of struggle and perseverance, and the ultimate hope in which all Christians share. They are reminding themselves of those who have gone before them and upon whose shoulders the current generation of Christians now stand and strive to participate in the Kingdom of God. They speak of a "great cloud of witnesses" who continues to encourage them in their current journey. I find it fitting that I, as a Christian scholar, use this opportunity to acknowledge the people who have encouraged me along the way in this leg of my journey; the first and foremost of which would be the one who has called me to be His follower.

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Dedicated to my wife, Carrie, and my children,
Korban, Kyler, Kane, and Carrigan Young

CHAPTER ONE

Introduction

In this chapter, I will provide an introduction to the current study by providing a brief review of key terms, a clear statement of the problem regarding individual differences and the prediction of accidents in early adulthood, and the purpose of the current study. I will conclude the chapter with the research questions guiding the current study.

Key Terms

Individual Differences

The study of *individual differences* within psychology is referred to as Differential Psychology (Tyler, 1965), and focuses on the psychological differences that exist between the individuals. Two specific areas of interest within this subfield of psychology include intelligence and personality (Maltby & Macaskill, 2007). Intelligence has been a topic of scientific investigation for over one hundred years (Brody, 2000; Cattell, 1988), and research into the measurement of intelligence has yielded a variety of theoretical models of intelligence that have been instrumental in its study (Carroll, 1993; Cattell, 1963; Horn and Cattell, 1966; Spearman, 1927). In addition to providing various models of the construct, research in the area of measured intelligence has also demonstrated that intelligence is related to many important life outcomes, such as aptitudes, leadership, genius, and income (Brand, 1987). Moreover, measures of intelligence serve as significant predictors of academic performance, job performance, and social behaviors (Gottfredson, 1997, 2002a, 2002b), as well as a variety of health - related outcomes (Deary & Batty, 2007).

A second primary area of research within Differential Psychology is personality. Modern personality research has its roots in some of the early works of Gordon Allport (1921; 1967), who worked diligently to clearly define personality research on which future research and applications of the research could build (Winter & Barenbaum, 1999). He eventually came to define personality traits from a behavioristic perspective, which suggests that personality is a function of habits that can be observed (Allport, 1967), and began to develop means for measuring the traits he saw as basic components of personality (Parker, 1991). By the end of the 20th Century, factor analytic procedures were providing a strong foundation for theoretical conceptions of personality (Winter & Barenbaum, 1999). The use of factor analysis has demonstrated a personality trait domain that can be broadly described by five primary traits (Goldberg, 1992; John, 1990; McCrae & Costa, 1999): Openness, Conscientiousness, Extraversion, Agreeableness, and Neuroticism. These traits have been referred to as the five factor model or the "Big Five" and have found a working consensus among most personality psychologists (Digman, 1989; McCrae & Costa, 1987; 1999).

Accidents

In its common usage, a*ccident* refers to a very large and nebulous set of events, only a small portion of which are injurious (Robertson, 2007). Even though it has had an assorted share of meanings throughout history (Loimer, Driur, & Guarnieri, 1996), it now primarily connotes a lack of intent when related to injuries. *Injury* refers to health outcomes that may or may not be associated with accidents, and has been a primary focus of the prevention literature. According to Finkelstein, Corso, and Miller (2006), about 77 percent of deaths and 36 percent of nonhospitalized injuries severe enough for their sufferers to seek medical attention in the United States are attributable to accidents with motor vehicles, firearms, falls, poisonings, fire/burns, and drowning. Included in these broader categories are incidents attributable to risky behaviors, such as drinking (Cherpitel, 2007) and fighting (Pickett, Craig, Harel, Cunningham, Simpson, Molcho, Mazur, Dostaler, Overpeck, & Currie, 2005), as well as assorted sports related injuries (Hopkins, Marshall, Quarrie, & Hume, 2007; Jones & Knapik, 1999; Watson, 1993). In the current study, *accident* will be used to describe incidence of injury that warranted some aspect of medical care.

In order to best address the prevention of injuries, there is an ongoing call from within the prevention and epidemiological communities to better understand the how injuries are reported, characterize the severity, and develop ongoing prevention strategies (Jones & Knapik, 1999). The accident literature has clearly established that accidents are not random occurrences, but that some individuals have more accidents than others. This finding holds even when the level of exposure to the same hazards in the same environment exist (Boyle, 1980; Hale & Glendon, 1987, pp. 314–316).

Cognitive Epidemiology: The Association between Individual Differences and Health Outcomes

Within the last decade, researchers have begun to use measures of intelligence to predict various health-related outcomes in an emerging sub-field called *cognitive epidemiology* (Deary & Batty, 2007). While much of the research in cognitive epidemiology has only occurred within the last decade, it has been quite successful in demonstrating that intelligence, whether measured in early childhood or late adulthood, is a significant predictor of various heath related outcomes; such as mortality (Batty, Deary, & Gottfredson, 2007; Hart et al., 2005; Kuh, Richards, Hardy, Butterworth, & Wadsworth, 2004), heart disease (Hemmingson, Melin, Allebeck, & Lundberg, 2006), and dementia (Snowdon, Kemper, Mortimer, Greiner, Wekstein, & Markesbery, 1996). While there are several hypotheses as to the underlying reasons why this intelligence-health outcome relationship exists, the current state of the field has not yet begun to tease apart support or refutation for the various hypotheses.

While most of the associations of intelligence with health outcomes and behaviors have been found to be independent of potentially confounding variables such as age, sex, and socioeconomic status, few researchers have investigated the role of personality factors as a potential mediating or moderating factor in health outcomes, particularly in relationship to health behaviors that might have long-term effects upon an individual's health, such as in the case of risky behavior and accidents. One exception is the "Terman Life Cycle of Children with High Ability" sample, which showed that conscientiousness, lack of cheerfulness, and permanence of mood were associated with living longer among people of higher cognitive ability (Schwartz, Friedman, Tucker, Tomlinson-Keasey, Wingard, & Criqui, 1995).

Adding to the argument for investigating personality traits alongside intelligence is that personality traits have been found to enhance predictive ability in important life outcomes such as job performance (Dunn, Mount, & Barrick, 1995; Ones, Viswesvaran, & Schmidt, 1993; Schmidt & Hunter, 2004), occupational level and income (Judge, Higgins, Thorensen, & Barrick, 1999), and health outcomes (Schwartz, Friedman, Tucker, Tomlinson-Keasey, Wingard, & Criqui, 1995). Personality traits have also been found to predict life outcomes such as mortality, divorce, and occupational outcomes better than other potential causes, such as socioeconomics (Roberts, Kuncel, Shiner, Caspi, & Goldberg, 2007). These findings, in addition to research suggesting personality trait measures stand as one of the two primary construct domains that account for much of the psychological variance in individuals (Austin et al., 2002), provide a significant basis for further investigation in their relationship to intelligence and health outcomes and behavior.

Statement of the Problem

There is an ongoing call from researchers within cognitive epidemiology to identify causal mechanisms and pathways that underpin the relationship between intelligence and health outcomes (Deary, Whiteman, Starr, Whalley, & Fox, 2004; Gottfredson & Deary, 2004). Likewise, in the broader research within all the social sciences, explaining causality has become a central topic over the last few decades. Kenny (2004) suggests that

> causal modeling should have a central position within social research for at least three reasons: (a) most researchers ether implicitly or explicitly construct models, a formal development of the method would assist these researchers, (b) casual modeling can assist the development, modification, and extension of measurement and substantive theory, and (c) casual modeling can give social sciences a stronger basis for applying theory to solving social problems. (p. 7)

The existing research in cognitive epidemiology has primarily focused upon health outcomes in later adult life, leaving a significant gap in the literature regarding the relationship of childhood intelligence and late adolescent/early adult health outcomes.

This is an important area to address, as it has the potential to provide early interventions for accidental injuries that can have ramifications lasting into later adulthood.

One specific health outcome that warrants extensive investigations is accidental injuries. According to a 2004 Centers for Disease Control report (CDC, 2004), unintentional injuries are a leading cause of death for Americans of all ages, regardless of gender, race, or economic status and millions of Americans sustain nonfatal injuries each year; in 2003, alone, more than 27 million people experienced a nonfatal unintentional injury serious enough to warrant a visit to an emergency room. In 1995, injuries were responsible for 147, 891 deaths, 2.6 million hospitalizations, and over 36 million emergency room visits (Fingerhut & Warner, 1997). Societal costs of injury-related deaths and medical care were estimated at $260 billion in the 1995 fiscal year (Bonnie, Fulco, & Liverman, 1999). The overwhelming number of injuries, the amount of money spent to treat the injuries, and the potential for long term effects due to injuries has prompted the call for more prevention research, within the United States (Bonnie, Fulco, & Liverman, 1999; CDC, 2004) and around the globe (Peden, McGee, & Sharma, 2002).

Purpose of Study

In this study, I will address gaps in the cognitive epidemiological literature by investigating the role of individual differences – specifically childhood intelligence and personality traits - in the prediction of accidents in early adulthood. This study adds to the ongoing research within the field of cognitive epidemiology by addressing the relationship between intelligence and health outcomes in late adolescence/early adulthood. Second, this research is designed as a response to the call for causal modeling within social science research, specifically within the field of cognitive epidemiology.

Research Hypotheses and Questions

The current research is governed by the hypothesis that intelligence in childhood does predict accidents in early adulthood, and seeks to investigate how personality traits relate to intelligence in their ability to predict accidents in early adulthood by asking the following research questions:

1. Does childhood intelligence predict accident incidence in early adulthood?
2. Does childhood intelligence predict accident incidence in early adulthood when controlling for childhood socioeconomic status and physical activity?
3. Does personality predict accident incidence in early adulthood?
4. How do particular personality traits influence the cognitive ability - accident incidence relationship?
    a. Do they add to the predictive ability?
    b. Do they moderate the relationship?
    c. Do they mediate the relationship?

CHAPTER TWO

Review of Literature and Key Terms

In this section, I will provide pertinent information regarding the literature associated with the current study. I will discuss how intelligence is characterized and understood throughout the reminder of the study, as well as its predictive strength with various life outcomes, including health outcomes. In addition, I will discuss how personality traits are defined and used in the current study, as well as how personality has demonstrated predictive strength with various life outcomes. Finally, I will discuss how accidents are understood in the current literature, and how they will be used in the current study.

History of Intelligence Research

Sir Francis Galton (1833-1911) is credited with being the pioneer of modern investigations into individual differences in intelligence (Jensen, 1998; Forrest, 1974), due to his extensive investigations regarding the hereditability of human abilities (Galton, 1869) and inquires into individual differences of sensory, motor, and mental capabilities (Galton, 1883). Galton's (1869) investigation led him to conclude that intelligence was a general phenomenon and rooted in biology. Moreover, he believed that any differences among individuals on this trait, as well as its influence on "real world phenomena" such as social reputations and propensity for hard work, were rooted in differences in inheritance, which allowed him to explain why some individuals achieve eminence and others do not.

In 1904, English psychologist Charles Spearman (1863-1945) published a paper where he reported the results of his investigation of Galton's observation that intelligent individuals had keener sensory discriminations than individuals who were of lower intelligence. After correcting for measurement errors, Spearman concluded that there were significant correlations between measures of sensory discrimination and mental ability, but he went a step farther than this and hypothesized that two related components of intelligence could be partitioned out of scores on measures of intelligence -- a general component (*g*), which he argued is measured to varying degrees by all tests of mental abilities, and a specific (*s*) component, which is only tapped by a particular test. Spearman wrote (1904):

> All branches of intellectual activity have in common one fundamental function (or groups of functions), whereas the remaining or specific elements of the activity seem in every case to be wholly different from that in all the others (p. 284).

In his research, he observed that not all tests of mental ability were equally correlated with one another, and, consequently, did not measure *g* to the same extent; that is, some tests were more "*g*-loaded" than others (the correlation of a particular test of mental ability with the *g* factor, the factor common to all tests in the analysis, is termed the test's *g* loading). Spearman's two-factor theory of intelligence was criticized and debated on conceptual (Thomson, 1916) and empirical (Thurstone, 1938) grounds, but researchers failed to displace or disprove the existence of *g* (Jensen, 1998).

One of the first significant variations to Spearman's two-factor model of intelligence proposed by Spearman came through the work of Raymond B. Cattell (1905-1998) and his student, John Horn (1928-2006) (Cattell, 1943, 1963, 1967; Horn & Cattell, 1967, 1982). Cattell (1943) proposed the existence of two types of adult mental capacities: a fluid intelligence (Gf) and a crystallized intelligence (Gc). In his theory (Cattell, 1943), fluid intelligence reflects the basic abilities used in reasoning and higher mental processes that require adaptation to new situations. In studies of large and diverse sets of ability, Gf emerges as closely related to Spearman's *g*, but it does not represent the entire repertoire of human intelligence (Horn, 1988). Crystallized intelligence, on the other hand, reflects what has been learned, based upon experiences, such as exposure to particular subjects in formal school settings. Measures of Gc are thus "a fallible indicator of the extent to which an individual has incorporated, through the systematic influences of acculturation, the knowledge and sophistication that can be referred to as the intelligence of a culture" (Horn, 1988, p.658-659).

According to Cattell (1963), individual differences in Gf and Gc are negligible before biological maturity (15-20 years old), reflecting mainly differences in cultural opportunity and interest. As formal learning and experience increases, the capacity for learning also increases (Cattell, 1963) and Gc becomes more independent of Gf (Horn and Cattell, 1966). In this manner, Gc is a function of Gf, in that fluid intelligence is "directly physiologically determined whereas Gc is a product of environmentally varying, experientially determined investments of Gf" (Cattell, 1963, p. 4). It follows from this that measurement in the earliest periods of life will show virtually no distinction between Gf and Gc (Horn, 1988). Horn, Donaldson, and Engstrom (1981) further suggest that as individuals grow older, the gap between Gf and Gc grows more significant due to varied experiences and the time decay of Gf.

In the 1990s, another significant variation of Spearman's original model came through the work of John B. Carroll (1916-2003). Carroll (1993) reanalyzed over 400 data sets of cognitive ability and developed what he referred to as a "three-stratum theory of cognitive abilities"(p. 633). His theory is based upon the results of factor analyses of multiple psychological tests and data obtained from observations of behaviors collected from sources such as school marks and ratings of competence. The result of Carroll's analyses is a thorough explication of abilities and processes related to intelligence that, in Carroll's (1993) accounting, consists of:

> …only one general ability, an ability that applies can be tested an ability that applies in varying degrees to all cognitive intellectual tasks. There are about ten broad abilities that apply to different domains of cognitive tasks. Finally, there are numerous abilities that apply to fairly specific kinds of cognitive tasks or performances, usually reflecting the effects of specialized learning or training (p. 713).

Whereas Cattell and Horn's model had distinguished between two types of general intelligence, Gf and Gc, Carroll's findings re - affirmed the existence of *g,* which stands at the apex of his three stratum model.

During the past decade, the Cattell – Horn (Horn, 1988) model of intelligence and Carroll's (Carroll, 1993) Three-Stratum models have been the most predominantly recognized models for understanding the structure of human intelligence by those within the psychometric community, and efforts have been made to combine the two models (McGrew, 2008). The combined model is referred to as the Cattell- Horn-Carroll (CHC) theory of intelligence (McGrew, 2008). While there are significant intrinsic differences between the two models, and disagreements regarding various abilities abound (Danthiir, Roberts, Pallier, & Stankov, 2001; McGrew, 2005; Stankov, 2000), their similarities have prompted several within the field of intelligence research to combine the two under one common nomenclature (McGrew, 2005).

Intelligence as a Predictor of Life Outcomes

Relationships that exist between measures of intelligence not only allow for the construction of models of intelligence, but they are also instrumental in demonstrating relationships with numerous life outcomes. In addition to being positively correlated to such desirable attributes as creativity, income, sense of humor, and social skills, measures of intelligence have also been shown to be negatively correlated to such negative outcomes as crime, delinquency, and impulsivity (for a more complete list, see Brand, 1987). Researchers have demonstrated that intelligence is not only correlated with several positive and negative attributes, but is a significant predictor of several life outcomes such as occupational attainment, education level, and socioeconomic achievement (Gottfredson, 1997; Gordon, 1997; Herrnstein & Murray, 1994; Jencks, 1979). This predictive relationship is strengthened when intelligence is measured by a test that is heavily g-loaded; that is, the test is a strong measure of general intelligence (Brand, 1987; Gottfredson, 2005; Jensen, 1980, 1998).

Intelligence and Academic Outcomes

The relationship between measures of intelligence and performance in various academic settings is one life outcome that has garnered significant research attention. Several detailed reviews of the early literature (Lavin, 1965; Matarazzo, 1972; Tyler, 1965) suggest that tests of intelligence are generally significant predictors of academic performance. While, some may question the reliability of the older studies due to the type of measure used, the lack of variance of intelligence within the groups tested, or both (Lavin, 1965), current research affirms that measures of general intelligence are the single best predictors of academic achievement (Gottfredson, 2002a; Kuncel, Hezlett, & Ones, 2004; Ones, Viswesvaran, & Dilchert, 2005).

More recent research suggests that general cognitive ability is correlated to the acquisition of concepts and knowledge related to curriculum in formal educational settings, even after controlling for variations in instructional methodology for delivering the content (Cronbach & Snow 1977) and is predictive of academic achievement (Fergusson, Horwood, & Ridder, 2005), even after partialling out variance due to specific areas of cognitive ability such as processing speed, working memory, and spatial ability (Rohde & Thompson, 2007). This predictive relationship tends not to decrease as the time between the administration of the measure of intelligence and the measures of academic achievement increases (Butler, Marsh, Sheppard, & Sheppard, 1985; Deary, Strand, Smith, & Fernandes, 2005; Feshbach, Adelman, & Fuller, 1977).

In addition to predicting academic achievement, cognitive ability is also a predictor of years of educational attainment, both within and between families (Jencks, 1979), which controls for potentially confounding cultural variables such as parental SES (Greany & Kellaghan, 1984). For example, Benson (1942) found that the correlation between test scores obtained in the sixth grade and the number of years of education that a person obtained was .57; that is, IQ accounted for nearly 36% of the variance between differences in educational attainment.

Intelligence and Employment Outcomes

Gottfredson (2003) suggests that "next to educational achievement, job performance has probably been the most exhaustively studied correlate of general intelligence" (p. 29). Research is consistent in demonstrating that general intelligence predicts training and job performance, as well as occupational level, about as well as, and sometimes better than, entire batteries of predictors that include personality traits, interests, and specific aptitudes (McHenry, Hough, Toquam, Hanson, & Ashworth, 1990; Schmidt & Hunter, 2004; Thorndike, 1986). This is important because success in training and acquisition of job knowledge predicts proficiency of individuals to perform job related tasks (Borman, White, Pulakos, & Oppler, 1991; Borman, Hanson, Oppler, Pulakos, & White, 1993; Borman, White, & Dorsey, 1995; Hunter, 1986; Schmidt, Hunter, & Outerbridge, 1986), independent of job experience, especially in more complex jobs (Borman et al., 1993; Schmidt et al., 1986). The value of *g* as a predictor of performance rises with the complexity of work (Hunter, 1986; Hunter, Schmidt, & Judiesh, 1990; McDaniel, Schmidt, & Hunter, 1988), the more specific the aspect of performance criterion being considered (McHenry, Hough, Toquam, Hanson, & Ashworth, 1990; Schmidt & Hunter, 2004), and the more objectively the performance is measured (Borman, White, Pulakos, & Oppler, 1991; Gottfredson, 2003; Hunter, 19986; Hunter & Schmidt, 1996).

Intelligence and Social Outcomes

Research has found that intelligence is a significant predictor of several social life outcomes, both positive and negative. For example, intelligence measured in childhood is predictive of such positive social outcomes as marriage by middle adulthood (Taylor et al., 2005), income level in adulthood (Fergusson, Horwood, & Ridder, 2005; Strenze, 2007), and social mobility at midlife (Deary et al., 2005). Moreover, it is a significant predictor of one's ability to carry out important daily life tasks, from being able to read and understand documents at work (Sticht, 1975) to self health care (National Work

Group on Literacy and Health, 1998). Intelligence predicts negative or socially undesirable outcomes, such as parental neglect (Brayden, Altemeir, Tucker, Deitrich, & Vietze, 1992; Crittenden, 1996), births out of wedlock (Herrnstein & Murray, 1986), and juvenile crime (Hirschi & Hindelang, 1977; Moffitt, Gabrielle, Mednick, & Schulsinger, 1981). Higher childhood cognitive ability is associated with receiving less practical and emotional support in later life, and being less satisfied with the support received (Bourne, Fox, Starr, Deary, & Whalley, 2007). The predictive power of intelligence tends to hold, even after controlling for potentially confounding variables such as SES, education, age, and race (Brand, 1987; Herrnstein & Murry, 1994).

Intelligence and Health Outcomes

Many of the life outcomes that intelligence predicts are related to, or potentially affect, one's socioeconomic status. Intelligence's relationship to these outcomes, as well as research suggesting a strong relationship between SES and health (Adler et al., 1994; Hayward, Crimmins, Miles, & Yang, 2000), has prompted the call for research investigating cognitive ability as a potential risk factor for health outcomes (Gottfredson, 2004b; Lubinski & Humphries, 1997). This field of research is referred to as cognitive epidemiology, and uses measures of individual differences, such as cognitive ability, as the primary variables of interest in studies of human health, disease outcomes, and mortality (Deary & Batty, 2007).

While the field of cognitive epidemiology is relatively new, investigations into the relationship between cognitive ability and health outcomes is not. Maller (1933), in one of the earliest investigations, found lower death rates in New York neighborhoods where children's mean IQ scores were highest. Studies by O'Toole, Adena, and Jones (1988), O'Toole (1990), and O'Toole and Stankov (1992) found positive associations between intelligence test scores and death rates for various causes among a sample of Australian Vietnam veterans. Using an exclusively female sample of nuns from the Nun Study, Snowdon, Greiner, Kemper, Nanayakkara, and Mortimer (1999) reported positive associations between measured cognitive abilities at approximately age 22 and age at death. Early studies from this longitudinal data demonstrated the predictive ability of measured intelligence and onset of dementia in old age (Snowdon, Kemper, Mortimer, Greiner, Wekstein, & Markesbery, 1996). Finally, the Malmo study in Sweden utilized a sample of individuals born between 1925 and 1929 and found 41 years later; scores on intelligence tests were inversely associated with mortality – that is, those with higher cognitive ability live longer (Furu, Lindegarde, Ljung, Munck, & Kristenson, 1985).

The health outcome most commonly examined in relation to individual differences is mortality. Cohort studies of older individuals indicate that those with higher IQ scores experience a lower risk of mortality (Korten et al., 1999) and that this predictive relationship holds when other potentially confounding health measures are considered, such as self-rated health, medication use, physical performance, functional limitations, lung function, and specific chronic diseases (Smits, Deeg, Kriegsman, & Schmand, 1999). Because IQ scores from older adults have the potential of being affected by previously existing health issues, referred to in the literature as comorbidity, investigators began using childhood intelligence test scores to predict mortality. Findings from studies using scores from both late adolescence and childhood IQ are consistent with much of the previous research using early and late adulthood measures of IQ: people with higher childhood intelligence tend to live longer (Batty, Deary, & Gottfredson, 2006; Hart et al., 2005; Hemmingson, Melin, Allebeck, & Lundberg, 2006; Kuh, Richards, Hardy, Butterworth, & Wadsworth, 2004), independent of potentially confounding environmental factors, such as childhood social position (Martin & Kubzansky, 2005; Silventoinen, Modig-Wennerstad, Tynelius, Rasmussen, 2007), and despite the various types of tests to used to measure cognitive ability (Batty, Deary, & Gottfredson, 2006).

While the relationship between intelligence and mortality has been the most thoroughly investigated health outcome in cognitive epidemiology, it is not the only health outcome. Other studies using IQ scores in adulthood found that IQ was also predictive of increased risk for schizophrenia, severe depression, and other forms of psychosis (Zammitt et al., 2004), as well as the possibility of improvement in cognition after hospitalization for schizophrenic episodes (van Winkel, Myin-Germeys, Delespaul, Peuskens, De Hert, & van Os, 2006). Investigations utilizing measures of childhood cognitive ability demonstrate that it is a significant predictor of anxiety and depression in women, and an increased risk for alcohol abuse in men and women (Hatch, Jones, Kuh, Hardy, Wadsworth, & Richards, 2007). Lower childhood cognitive ability is a significant predictor of cognitive decline in later adulthood, suggesting that people with lower mental ability scores demonstrated greater cognitive decline (Bourne, Fox, Deary, & Whalley, 2007). Childhood IQ is also a significant predictor of accidental injuries in adulthood (Lawlor, Clark, & Leon, 2007), blood pressure at midlife (Starr et al., 2004), accelerated progression of AIDS (Farinpour et al., 2003), and early adult illnesses (Martin, Fitzmaurice, Kindlon, & Buka, 2004).

Negative health outcomes are not the only focus of the intelligence – health outcome research. Childhood IQ measures have been found to predict good health behaviors such as a healthy diet and exercise (Batty, Deary, Schoon, & Gale, 2006), adherence to medical advice (Stilley, Sereika, Muldoon, Ryan, & Dunbar-Jacob, 2004), and likelihood of abandoning unhealthy habits, such as smoking, in adulthood (Taylor et al., 2003). This corpus of findings provides a strong rationale for the use of measured intelligence, whether measured in childhood, late adolescence, or later adulthood, as a significant predictor of various health outcomes (Lubinski & Humphreys, 1997).

Mechanisms for IQ-Health Relationship

Whalley and Deary (2001) suggest four possible mechanisms relating childhood IQ to longevity in adulthood: childhood IQ might be (a) an archeological record of prior (prenatal and childhood) insults, such as maternal alcohol usage during prenatal development or low birth weight, (b) a record of the integrity of the entire body, (c) a predictor of healthy behaviors (e.g., injury avoidance, do not smoke), and (d) a predictor of entry into healthy environments (e.g., selecting safer work environments).
These mechanisms may not work independent of one another, but may serve as mediators or moderators of the intelligence-health outcomes relationship.

To date, research investigating the mechanisms underlying the IQ-health associations suggest that paternal social class around the time of birth, number of previous births, maternal physical condition, whether the child was born outside of marriage, prematurity, intrauterine, and childhood height are all independently associated with childhood intelligence, with social class providing the strongest association (Lawlor et al., 2004). Another study by Walker, Thame, Chang, Bennett, and Forrester (2006) found a few associations between growth *in utero* and cognition, but more research is needed in this area to better understand this relationship. A small, consistent positive association between birth weight and childhood cognitive ability was found among six studies included in a systematic review by Shenkin, Starr, and Deary (2004). This same review found that parental social class accounted for a larger proportion of variance than birth weight, and that these two variables were largely independent.

Gottfredson (2004) and Gottfredson and Deary (2004) have argued that the technological advances in modern cultures produce a level of complexity in regard to self healthcare and that the rise in complexity requires higher cognitive functioning. Thus, higher cognitive functioning becomes increasingly important for maintaining good health. While this has some support from studies of patients with hypertension and diabetes (Williams, Baker, Parker, & Nurss, 1998) and treatment of common chronic illnesses (Salomaa et al., 2001), other research argues that this association does not always hold (Singh-Manoux, Ferrie, Lynch, & Marmot, 2004).

History of Personality Research

Modern personality research has its roots in some of the early works of Gordon Allport (1921; 1967), in which he focused on the distinctions between personality and character; and attempted to define personality on which future research and application could build (Winter & Barenbaum, 1999). Allport eventually came to define personality traits from a behavioristic perspective, conceptualizing traits as a system of habits (Allport, 1967) and began to develop means for measuring the traits he saw as basic components of personality (Parker, 1991). After studying in Germany and returning to America to teach, Allport continued to refine his definition of traits (1931, 1937). He sought to define and systematize the field of personality psychology in order to provide a coherent grouping of concepts and theories (Winter and Barenbaum, 1999). He accomplished this through what has been termed a *lexical* study of traits; a systematic list of descriptive terms for behaviors that were grouped together to form the basis of future personality research (Allport & Odbert, 1936).

The lexical approach to the study of personality provided an enormous array of data for the personality psychologists of the day. Raymond Cattell (1946) sought to provide for a coherent organization of this data through correlations and multivariate techniques. Using peer ratings of 208 men on 35 trait-paired clusters from the Allport and Odberg (1936) list of 4, 504 traits, Cattell's factor analysis yielded 12 primary factors, which were consistent with studies carried out by other investigators. He (1946) concluded that his 12 factors represented the primary traits. While his factor analytic approach to studying personality set the stage for future personality research, it was not with out controversy (Winter and Barenbaum, 1999). For example, Hans Eysenck (Eysenck & Eysenck, 1985) argued that Cattell's 12 oblique factor rotations were equivalent to his the orthogonal "superfactors" of Extraversion, Neuroticism, and Psychoticism. While debates regarding the use of factor analysis and the various rotational approaches continued, by the end of the 20^{th} Century, many personality psychologists had reached a working consensus that the trait domain could be broadly described by five orthogonally rotated factors or clusters of traits (Goldberg, 1992; John, 1990; McCrae & Costa, 1999): Openness, Conscientiousness, Extraversion, Agreeableness, and Neuroticism. These traits have been referred to as the five factor model or the "Big Five" (Digman, 1989; McCrae & Costa, 1987; 1999)

Interpreting the "Big Five"

Several analyses of personality inventories support what has been referred to as the "Big Five" factors of personality (McCrae & Costa, 1987; 1999); these factors are Openness(O), Conscientiousness (C), Extraversion (E), Agreeableness (A), and Neuroticism (N), and have been summarized by Digman (1989, p. 200-202) in the following manner:

1. *Openness (O)* – As one of the more difficult factors to define, a high openness score appears to be related to one's openness to new ideas, other's values, and one's own feelings. It is also related to one's willingness to learn and experience new things, and, as such, has often been related to intellect (Digman & Inouye, 1986).
2. *Conscientiousness (C)* – A high score on measures of Conscientiousness suggests a deep sense of reliability and responsibility.
3. *Extraversion (E)* - High scores of Extraversion suggest an enthusiastic, encounter with oneself and one's life circumstances.
4. *Agreeableness (A)* – High scores in this factor suggest a strong inclination toward submission to others, whether they are peers or individuals in authority. It is not just the tendency to agree with others (Goldberg, 1981; McCrae, & Costa, 1987; Tupes & Christal, 1961).
5. *Neuroticism (N)* – This factor covers a broad variety of characteristics that appear to be related to some aspect of anxiety within the individual or one's propensity toward anxiety.

Personality and Life Outcomes

Personality measures have been found to be meaningful predictors of important life outcomes such as job performance (Dunn, Mount, & Barrick, 1995; Ones, Viswesvaran, & Schmidt, 1993; Schmidt & Hunter, 2004), occupational level and income (Judge, Higgins, Thorensen, & Barrick, 1999), and academic success (Chamorro - Premuzic & Furnham, 2003; Nguyen, Allen, & Fraccastoro, 2005). They have also been found to predict various health outcomes, such as mortality (Schwartz, Friedman, Tucker, Tomlinson-Keasey, Wingard, & Criqui, 1995), accident involvement in occupational and non-occupational settings (Clark & Robertson, 2005; Sümer, Lajunen, & Özkan, 2005), and self-reported health behaviors and outcomes at mid-life (Hampson, Goldberg, Vogt, & Dubanoski, 2006).

Accidents

In its common usage, a*ccident* refers to a very large and nebulous set of events, only a small portion of which are injurious (Robertson, 2007). Even though it has had an assorted share of meanings throughout history (Loimer, Driur, & Guarnieri, 1996), it now primarily connotes a lack of intent. What typically is the focus of the prevention literature is the term "injury" or a reference to specific types of injury (Robertson, 2007). According to Finkelstein, Corso, and Miller (2006), about 77 percent of deaths and 36 percent of nonhospitalized injuries severe enough for their sufferers to seek medical attention in the United States are attributable to incidents with motor vehicles, firearms, falls, poisonings, fire/burns, and drowning. Included in these broader categories are incidents attributable to risky behaviors, such as drinking (Cherpitel, 2007) and fighting (Pickett, Craig, Harel, Cunningham, Simpson, Molcho, Mazur, Dostaler, Overpeck, &

Currie, 2005), as well as assorted sports related injuries (Hopkins, Marshall, Quarrie, & Hume, 2007; Jones & Knapik, 1999; Watson, 1993). In order to best address the prevention of injuries, there is an ongoing call from within the prevention and epidemiological communities to better understand the surveillance of incidence, characterize the severity, and develop ongoing prevention strategies (Jones & Knapik, 1999).

The accident literature has clearly established that accidents are not random occurrences, but that some individuals have more accidents than others. This finding holds even when the level of exposure to the same hazards in the same environment exist (Boyle, 1980; Hale & Glendon, 1987, pp. 314–316). While constraints have made it difficult to parse out which individual differences are most pertinent for accident prevention, accident research has demonstrated that the risk of accidents is higher among workers who have less experience in the task at hand or when tasks are more complex (Boyle, 1980; Hale & Hale, 1972); a pattern similar to the relationship with intelligence and job performance. The more complex a problem, the more general mental ability, or mental competence, needed (Gottfredson, 2004a)

The real question regarding accidents is not what causes them, but how to prevent them. Hale and Glendon (1987) suggest that this begins with a system under control; that is, people consistently and constantly pay attention to potential safety threats. This requires an enormous amount of energy, attention, and effort, all of which increases as the level of task complexity, time pressure, and level of distractions increase. Therefore, the control of a system, and, therefore, the prevention of accidents requires an enormous amount of cognitive competence (Gottfredson, 2004a).

Purpose of Study

In this study, I will address gaps in the cognitive epidemiological literature by investigating the role of individual differences – specifically childhood intelligence and personality traits - in the prediction of accidents in early adulthood. This study adds to the ongoing research within the field of cognitive epidemiology by addressing the relationship between intelligence and health outcomes in late adolescence/early adulthood. Second, this research is designed as a response to the call for causal modeling within social science research, specifically within the field of cognitive epidemiology.

Research Hypotheses and Questions

The current research is governed by the hypothesis that intelligence in childhood does predict accidents in early adulthood, and seeks to investigate the relationship of personality traits to intelligence and their predictive relationship with accidents in early adulthood by asking the following research questions:

1. Does childhood intelligence predict accident incidence in early adulthood?
2. Does childhood intelligence predict accident incidence in early adulthood when controlling for childhood socioeconomic status and physical activity?
3. Does personality predict accident incidence in early adulthood?
4. How do particular personality traits influence the cognitive ability - accident incidence relationship?
    a. Do they add to the predictive ability?
    b. Do they moderate the relationship?
    c. Do they mediate the relationship?

CHAPTER THREE

Methods

In this chapter, I will provide the research questions that guide the current study, background information regarding the design and study population, the instruments used to measure the various constructs, and how missing data was handled. The chapter concludes with an overview of the analytic methods used to investigate the predictive relationships of interest.

Research Questions

The current research is governed by the hypothesis that intelligence in childhood does predict accidents in early adulthood, and seeks to investigate the relationship of personality traits to intelligence and their predictive relationship with accidents in early adulthood by asking the following research questions:

1. Does childhood intelligence predict accident incidence in early adulthood?
2. Does childhood intelligence predict accident incidence in early adulthood when controlling for childhood socioeconomic status and physical activity?
3. Does personality predict accident incidence in early adulthood?
4. How do particular personality traits influence the cognitive ability - accident incidence relationship?
   a. Do they add to the predictive ability?
   b. Do they moderate the relationship?
   c. Do they mediate the relationship?

Background Information

Study Design

The current study is a retrospective analysis of the predictive relationship between individual differences and accidents in early adulthood using data from the Longitudinal Study of Adolescent Health (Add Health; Udry & Bearman, 1998). The Add Health study was designed as a multi-wave complex survey (Lehtonen & Pahkinen, 2004). The data supplies cluster, strata, and sample weights for participants who provided needed information at Waves I and III (Add Health, 2004). When the complex nature of the survey is accounted for in the analysis, the14, 322 respondents provide a nationally representative sample of the 1995 population of American adolescents.

Study Population

The current study used data from the National Longitudinal Study of Adolescent Health (Add Health; for more on its research design, see Udry & Bearman, 1998). The Add Health study was initiated in 1994 under a grant from the National Institute of Child Health and Human Development (NICHD) with co-funding from 17 other federal agencies. It is designed to be the largest, most comprehensive survey of adolescents ever undertaken to study the health related behaviors of adolescent male and females, grades 7 through 12, and their outcomes in young adulthood. The first wave (Wave I) of data collection was conducted in two stages between September 1994 and December 1995. In 2001 and 2002, Add Health respondents, now 18 to 26 years old, were re-interviewed (Wave III) to investigate the health status of the sample in young adulthood. Data from Wave I and Wave III are used in the current study.

The first wave of data collection began with sampling 80 high schools for in-school data collection. The 80 high schools selected were stratified in a manner to assure they were representative of US schools in urbanicity (e.g. urban versus rural), region of country, size, type, and ethnicity. Seventy - percent of the schools from the original sample participated in the study and schools that declined the opportunity to participate were replaced with by schools within the stratum. Participating high schools assisted in identifying feeder schools – that is, schools that included a seventh grade and that matriculated at least five students to the secondary level. From the identified feeder schools, only one was selected for participation, based upon the proportion of students it sent to the high school. Similar to the process with recruiting high school participation, if feeder schools declined to participate per high school, a suitable replacement was selected. In the end, 132 schools, and more than 90,000 students were included in the core study.

All students who completed the In–School Questionnaire, plus those who may not have completed the questionnaire but were listed on a school roster, were eligible for inclusion in the core in-home sample. Students in each school were stratified by grade and sex. Seventeen students were randomly selected from each stratum so that a total of approximately 200 7^{th} though 12^{th} grade students were selected from each of the 80 participating schools. A total sample of 18, 924 students were interviewed in their homes, which includes oversampled special populations. Table 1 includes the *n* for the oversampled populations.

Table 1
Oversampled Populations

Population	*n*
Disabled	2,559
Blacks from well-educated families	471
Chinese	1,038
Cuban	334
Puerto Rican	437
Adolescents residing together- Twins	1, 981
Adolescents residing together- Full siblings	1186
Adolescents residing together- Half siblings	783
Adolescents residing together- Non related	415
Adolescents residing together- Sibling of twins	162

In 2001, the Add Health research team began data collection for Wave III. The sample for this wave of data collection, now between the ages of 18 and 26 years old, consisted of respondents from the first wave that could be located and re-interviewed during the collection period. There were 14, 322 students that had data from both Wave I and Wave III that were used for this study.

Instruments

In order to model the predictive ability of individual differences on accident incidence in early adulthood, several measures are needed. The Add Health Picture Vocabulary Test (AHPVT) was used as a measure of cognitive ability; the Bem Sex Role Inventory (BSRI) was used as a composite personality measure, and several survey questions related to personality constructs were used as proxies for measuring Extraversion, Neuroticism, and Conscientiousness. The combination of several income variables are used as a measure of childhood socioeconomic standing (SES). In addition, several questions related to physical activity (PA) were used as a covariate, and questions from the In-Home Questionnaire about individual hospital and emergency room visits were used as the dependent variable.

Add Health Picture Vocabulary Test (AHPVT)

The Peabody Picture Vocabulary Test - Revised (PPVT – R; Dunn & Dunn, 1981) was originally designed to measure hearing vocabulary for Standard American English. The Add Health Picture Vocabulary Test (AHPVT) is an adapted version of the PPVT-R consisting of half the items from the original PPVT-R (the odd numbered panels from items 1 to 87 and even-numbered panels from 90 to 75) and is used in this study as a measure of intelligence. Correspondence between the PPVT – R and the AHPVT were tested and scores from the two administration techniques yielded a correlation of .96 (Halpern, Joyner, Udry, & Suchindran, 2000). As in the administration of the PPVT – R, the Add Health interviewer reads a word and the respondent selects, from among four simple illustrations, the picture that best illustrates the word. The AHPVT illustrations were the same ones used in the PPVT – R. While the Add health data contains raw and standardized AHPVT scores, the scores used for this analysis are the age-corrected Wave I scores that use the Wave III sample weights - the AHPVT variable recommended for usage by the authors of the Add Health study (Carolina Population Center, 2003, p. 4).

Dunn and Dunn (1981) report internal consistencies from .61 to .88 and alternate form reliability values from .71 to .91 from their standardization sample.

Furthermore, they report positive correlations ranging from .16 to .78 between the PPVT-R and other vocabulary tests and tests of general intelligence, such as the Wechsler series and Stanford-Binet. The use of this test as a valid measure of cognitive ability is bolstered from other research showing the potency of literacy as a measure of cognitive ability (Gottfredson, 2004), and some even advocate its usage over other measures when using a sample of highly diverse individuals (Manly, Touradji, Tang, & Stern, 2003). Table 2 shows the number of studies, cases, and correlations of the PPVT-R with six widely used tests of intelligence.

Table 2
Correlation of PPVT – R with Other Intelligence Tests

Test	Studies	Cases	*r*
Kaufman Adolescent and Adult Intelligence Test			
Composite IQ	2	192	0.76
Crystallized IQ	2	192	0.78
Fluid IQ	2	192	0.67
Ravens Progressive Matrices			
Standard Progressive Matrices	1	60	0.66
Coloured Progressive Matrices	2	60	0.56
Stanford-Binet Intelligence Scale- 4th Ed.			
Composite	8	424	0.58
Verbal	5	329	0.69
Abstract/Visual	5	329	0.43
Quantitative	4	208	0.29
Short-Term Memory	5	329	0.44
Abbreviated Battery	2	54	0.59

(table continues)

Test	Studies	Cases	*r*
Slossan Intelligence Test	1	100	0.48
Wechsler Adult Intelligence Scale-Revised			
FSIQ	6	314	0.73
VIQ	5	283	0.74
PIQ	4	262	0.64
Wechsler Intelligence Scale for Children-Revised			
FSIQ	18	1,099	0.70
VIQ	20	1,345	0.69
PIQ	17	1,034	0.51
Woodcock-Johnson- Revised			
Broad Cognitive Ability	1	64	0.69

Note. Adapted from "Technical Reference to the PPVT – III" by K. T. Williams and J. J. Wang, 1997, p. 45. Copyright 1997 by the American Guidance Service, Inc.

Bem Sex Role Inventory (BSRI)

Bem Sex Role Inventory (BSRI) data was collected at in-home interviews with a sub-sample of participants who were in relationships during Wave III. Researchers used the short form of the BSRI, which consists of 30 questions – 10 questions measuring masculinity, 10 questions measuring femininity, and 10 questions that served as filler intended to not measure anything of significance. The BSRI (Bem, 1974) was initially developed to measure a proposed two-factor structure of masculine and feminine traits: masculinity and femininity. Several studies have demonstrated that the BSRI has shown considerable overlap with Big Five dimensions of personality (Digman, 1989). Specifically, research suggests that high scores on the Masculinity scale of the BSRI have high positive correlations with Extraversion and Openness and negative correlations with Neuroticism, while a high score on the Femininity scale was primarily related to

Agreeableness and Conscientiousness (Lippa, 1991; 1995; 2001). These findings have also been found to hold in cross cultural validation studies (Marušić & Bratko, 1998). For this study, higher scores on the Masculinity scale suggest that those individuals tend to exhibit high tendencies of Extraversion and Openness, and are low in Neuroticism. As scores increase on the Femininity scale, those individuals tend to exhibit higher tendencies toward Agreeableness and Conscientiousness.

Composite Personality Variables

Composite personality variables were created from several questions from the In-Home Questionnaire and In-School Questionnaire from Wave I. This was accomplished by mapping various questions from the Add Health surveys that were related to personality and behaviors onto a well established instrument for measuring personality: the NEO-PI-R (Costa & McCrae, 1992). The questions from the Add Health surveys and how they were mapped onto the NEO-PI-R (Costa & McCrae, 1992) for each personality trait are found in the Appendix A.

To assess unidimensionality of the Add Health personality variables, the items for each personality trait were first correlated, and then within each personality domain (e.g. Neuroticism, Extraversion, and Conscientiousness) items were subjected to a principal component analysis (PCA). PCA is a mathematical procedure that transforms correlated variables into a smaller number of unrelated variables called *principal components* (Jackson, 1991). The first, or primary, component accounts for as much of the variability in the data as possible, and each component thereafter accounts for as much of the remaining variability as possible, under the constraint of being orthogonal to the previously extracted component(s). The primary goal of PCA is to reduce the dimensionality of a dataset. Tables 3 through 5 provide the correlations for each of the variables by personality domain. Table 6 lists the first component loadings for each of the personality construct variables, as well as the total variance explained. Component scores were developed using regression methods and were used as the personality variables.

Table 3
Correlation Matrix for Neuroticism Variables

Variable	1	2	3	4	5	6
1. H1PF10	1.00					
2. H1PF 30	0.13	1.00				
3. H1PF 32.	0.17	0.65	1.00			
4. H1PF33	0.24	0.47	0.56	1.00		
5. H1PF34	0.25	0.41	0.48	0.57	1.00	
6. H1PF36	0.13	0.53	0.60	0.52	0.48	1.00

Table 4
Correlation Matrix for Extraversion Variables

Variables	1	2	3	4	5	6	7
1. H1PF35	1.00						
2. H1DS15	0.09	1.00					
3. H1NB1	0.15	0.11	1.00				
4. S44A32	-0.06	-0.03	0.02	1.00			
5. S62B	0.24	0.06	0.06	0.04	1.00		
6. S62E	0.22	0.06	0.08	-0.08	0.55	1.00	
7. S62O	0.35	0.06	0.08	-0.03	0.43	0.46	1.00

Table 5
Correlation Matrix for Conscientiousness Variables

Variables	1	2	3	4	5	6
1. H1PF8	1.00					
2. H1PF14	0.09	1.00				
3. H1PF18	0.28	0.14	1.00			
4. H1PF19	0.24	0.14	0.49	1.00		
5. H1PF20	0.23	0.18	0.44	0.48	1.00	
6. H1PF21	0.24	0.15	0.41	0.44	0.45	1.00

Table 6
Component Loadings and Variance Explained for Composite Personality Variables

Variable	Component Loading	% Variance Explained
Neuroticism		51.00
(H1PF10) You never get sad.	0.35	
(H1PF36) You feel loved and wanted.	0.76	
(H1PF 30) You have a lot of good qualities	0.74	
(H1PF 32) You have a lot to be proud of.	0.82	
(H1PF33) You like yourself just the way you are.	0.78	
(H1PF34) You feel like you are doing everything just about right	0.74	
Extraversion		32.83
(H1PF35) You feel socially accepted.	0.58	
(H1NB1) You know most of the people in your neighborhood	-0.24	
(S62B) How strongly do you agree or disagree with the following statements? I feel close to people at school.	0.78	

(table continues)

Variable	Component Loading	% Variance Explained
(S62E) How strongly do you agree or disagree with the following statements? I feel like I am a part of this school.	0.80	
(S62O) How strongly do you agree or disagree with the following statements? I feel socially accepted.	0.58	
(S44A32) Here is a list of clubs, organizations, and teams found at many schools. Darken the oval next to any of them that you are participating in this year, or that you plan to participate in later in the school year. Student Council.	-0.15	
(H1DS15) In the last 12 months, how often did you act loud, rowdy, or unruly in a public place?	0.13	
Conscientiousness		40.00
(H1PF21) After carrying out a solution to a problem, you usually try to analyze what went right and what went wrong.	0.70	
(H1PF18) When you have a problem to solve, one of the first things you do is get as many facts about the problem as possible.	0.75	
(H1PF19) When you are attempting to find a solution to a problem, you usually try to think of as many different ways to approach the problem as possible.	0.77	
(H1PF20) When making decisions, you generally use a systematic method for judging and comparing alternatives.	0.74	
(H1PF8) When you get what you want, it's usually because you worked hard for it	0.44	
(H1PF14) You usually go out of your way to avoid having to deal with problems in your life.	0.18	

Childhood Socioeconomic Status

Childhood socioeconomic status (SES) was measured by creating a composite variable from various questions from Wave I related to family income and government aid. All questions used to form the SES variable were submitted to a PCA. One component was extracted and the component scores were used as the study's SES variables. The questions used to form the childhood SES variable can be found in Appendix A and the specific variables used in the PCA, component loadings, and total variance explained are listed in Table 7.

Table 7
Component Loadings and Variance Explained for Childhood SES Variable

Variable	Component Loading	% Variance Explained
Childhood SES		41.94
(PA55) About how much total income, before taxes, did your family receive in 1994?	-0.43	
(PA57) Last month, did you or any member of your household receive:		
(B) Supplemental Security Income (SSI)?	0.50	
(C) Aid to Families with Dependent Children (AFDC)?	0.79	
(D) Food stamps?	0.84	
(F) A housing subsidy or public housing?	0.58	

Physical Activity Variables

Physical activity variables were created from questions in the In-Home Questionnaire (Wave III) that asked the respondent about the type and frequency of various physical activities in which s/he was involved. Response options ranged from 0 to

7. Questions were then weighted by metabolic units above resting (MET) intensity values from the updated Compendium of Physical Activities (CPA; Ainsworth et al., 2000), which was developed to facilitate standardized coding of physical activities obtained from record keeping. MET values are the ratio of work metabolic rate to a standard resting metabolic rate of 1.00.; 1 MET is considered the resting metabolic rate level obtained during quiet sitting (Ainsworth et al., 2000). Survey questions used are listed Appendix A.

Each activity listed in each question was given a MET value based upon the CPA, and then a mean MET value was calculated for each question. For example, "In the past seven days, how many times did you bicycle, skateboard, dance, hike, hunt, or do yard work?" lists the activities of bicycling, skateboarding, dancing, hiking, hunting, and yard work. Each activity would be given a MET value and then the mean of the values would be considered the overall MET value for that particular question. Each question was then assigned a categorical value based upon the level of intensity as prescribed by Pate, Pratt, Blair, et al. (1995): light, < 3 METs; medium, 3-6 METS; and vigorous, > 6 METs (Table 3.5). Table 8 shows the MET values assigned to each activity listed in each physical activity question.

The six weighted activity variables were then subjected to a PCA, extracting both one and two components. When extracting one component, all component loadings were between .53 - .68, and that component explained approximately 40% of the total variance. For the two-component extraction, the loadings ranged from -.16 - .68, but did not form a discernable pattern. That is, they did not differentiate themselves based on the moderate-vigorous dichotomization.

Table 8
MET Values and Intensity Levels for Activity Questions

Question	Activities	METs	Average METs	Intensity
(H3DA8) In the past seven days, how many times did you bicycle, skateboard, dance, hike, hunt, or do yard work?	Bicycle	8.00	5.90	Moderate
	Skateboard	5.00		
	Dance	6.50		
	Hike	6.00		
	Hunt	5.00		
	Yard work	5.00		
(H3DA9) In the past seven days, how many times did you roller blade, roller skate, downhill ski, snow board, play racquet sports, or do aerobics?	Roller blade	12.50	7.75	Vigorous
	Roller skate	7.00		
	Downhill ski	6.00		
	Snow board	7.00		
	Racquet sports	7.00		
	Aerobics	7.00		
A10) In the past seven days, how many times did you participate in strenuous team sports such as football, soccer, basketball, lacrosse, rugby, field hockey, or ice hockey?	Football	8.00	7.86	Vigorous
	Soccer	7.00		
	Basketball	6.00		
	Lacrosse	8.00		
	Rugby	10.00		
	Field hockey	8.00		
	Ice hockey	8.00		
(H3DA11) In the past seven days, how many times did you participate in individual sports such as running, wrestling, swimming, cross-country skiing, cycle racing, or martial arts?	Running	7.00	8.30	Vigorous
	Wrestling	6.00		
	Swimming	7.00		
	Cross country skiing	8.00		

(table continues)

Question	Activities	METs	Average METs	Intensity
	Cycle racing	12.00		
	Martial arts	10.00		
(H3DA12) In the past seven days, how many times did you participate in gymnastics, weight lifting, or strength training?	Gymnastics	4.00		
	Weight lifting	3.00	4.30	Moderate
	Strength training	6.00		
(H3DA13) In the past seven days, how many times did you play golf, go fishing or bowling, or play softball or baseball?	Golf	4.50		
	Fish	3.00		
	Bowl	3.00	4.10	Moderate
	Softball	5.00		
	Baseball	5.00		

Moreover, the second component only explained an additional 16% of the total variance. Consequently, all the variables were combined into one activity variable, which were the scores extracted from the first component. Table 9 shows the specific variables used in the PCA, component loadings, and total variance explained.

Accident Variables

In Wave III of the Add Health data, participants reported on numerous health outcomes, including number of visits to doctor offices, emergency rooms, and hospital stays, as well as the reason for the visits. For this study, four different questions regarding accidents were used, indicating having or not having an accident. The accident variables, as well as the questionnaires and sections from which they originated are found in Appendix A.

Table 9
Component Loadings and Variance Explained for Physical Activity Variable

Variable	Component Loading	% Variance Explained
Physical Activity		40
(H3DA8) In the past seven days, how many times did you bicycle, skateboard, dance, hike, hunt, or do yard work?	0.56	
(H3DA9) In the past seven days, how many times did you roller blade, roller skate, downhill ski, snow board, play racquet sports, or do aerobics?	0.64	
(H3DA10) In the past seven days, how many times did you participate in strenuous team sports such as football, soccer, basketball, lacrosse, rugby, field hockey, or ice hockey?	0.65	
(H3DA11) In the past seven days, how many times did you participate in individual sports such as running, wrestling, swimming, cross-country skiing, cycle racing, or martial arts?	0.68	
(H3DA12) In the past seven days, how many times did you participate in gymnastics, weight lifting, or strength training?	0.68	
(H3DA13) In the past seven days, how many times did you play golf, go fishing or bowling, or play softball or baseball?	0.53	

Missing Data

Missing data is a common problem in quantitative research (Little & Rubin, 2002). According to Rubin's theoretical framework (1976), there are three mechanisms to classify why data are missing: *missing completely at random* (MCAR), *missing at random* (MAR), and *not missing at random* (NMAR). In brief, the MCAR mechanism is when missing values on a particular variable specifying, *X,* are uncorrelated to other variables in the data set as well as the underlying values of *X* itself. The MAR mechanism is when missing values for variable *X* can be related to other measured variables in the data set, but are still unrelated to the underlying values of *X*. The MNAR mechanism (sometimes called non – ignorable) results whenever the probability of missing values of *X* is directly related to the underlying values of *X*. These underlying mechanisms dictate the optimal method for handling missing data, although it should be noted that all three may be present in a given data set (Yuan & Bentler, 2000).

Some of the more robust methods for dealing with missing data (e.g., multiple imputation [MI] or maximum likelihood [ML]) require the MAR assumption and will, in turn, produce parameter estimates that are unbiased and efficient when data are MAR or MCAR. On the other hand, traditional methods (e.g., listwise deletion) generally require MCAR data and will generally produce biased parameter estimates under MAR (Peugh & Enders, 2004).

Missingness was assessed for MCAR using Little's (1988) χ^2. The results suggest that the missing data are not MCAR, χ^2 (df = 3935) = 7632.006, $p \leq .000$. It was then determined, following Switzer & Roth (2002), to impute the missing values for all variables used in the analysis, with the exception of the BSRI data. The BSRI data was not imputed because it was not administered to the entire study population. It was only administered to a sub – sample of the Add Health participants who were involved in a relationship at Wave III. Table 10 shows the missingness for each variable.

MI is a three step procedure that involves (1) creating *m* imputed datasets that have different imputed values for every missing value; (2) analyzing the *m* datasets, saving parameter estimates and standard errors from each analysis; and (3) pooling the parameter estimates and standard errors from the *m* data sets to arrive at a single set of parameter estimates and corresponding standard errors (Graham, Cumsille, & Elek-Fisk; 2003). In the current study, 10 imputed data sets were generated. MI was conducted using the IVEware imputation and variance estimation software (Raghunathan, Solenberger, & Hoewyk, 2002) because it allows for the imputation of categorical variables. The 10 datasets were analyzed and the parameter estimates and standard errors for each data set were combined into a single set of parameter estimates and standard errors. It was this newly created, single set of parameter estimates and standard errors that are reported as the study's outcome.

Analysis

Data was analyzed in M*plus* 5.0 (Muthén & Muthén, 1998 - 2007) using a probit regression model with latent outcome using Muthen's WLSMV estimator. All variables were mean centered (i.e., $\overline{X}$ = 0), with the exception of the accident variables, and entered into the analyses according to the research questions. Mean centering helps interpretation because the zero - point is the average of the variable (Gelman, 2007; Kreft, Kreft, & de Leeuw, 1998). The research questions and accompanying path analyses are shown in figures 1 - 6. Note that for each accident variable represented in the path models, there are four different Add Health variables. So each model will be analyzed 4 times, once for each accident outcome.

Because each accident variable is dichotomous, a probit transformation was used for all analyses, which transforms the binary nature of the dependent variable into a normal distribution using a cumulative normal distribution function (Agresti & Natarajan, 2001; Hedeker, 2008; Snijders & Bosker, 1999).

What follows is a brief discussion of how Mplus characterizes probit regression models, as well as the use of a latent response variable in the probit model that was used to analyze the data for the current study. The content is from Muthén's (1998 – 2004) Technical Appendices for Statistical Analysis with Latent Variables.

Table 10
Missing Data for Variables Used

Variable	N	Missing	% Missing
Cognitive Ability			
PPVT_IQ	13174	1148	8.00
Personality			
BEMMale	3938	10384	72.50
BEMFemale	3942	10380	72.50
EXVSN	9736	4586	32.00
NEUROT	14254	68	.50
CONSC	14129	193	1.30
SES			
Parent_SES	10400	3922	27.40
Physical Activity			
PA	14267	55	.40
Accidents			
ACCIDENT 1	3349	10973	76.60
ACCIDENT 2	14127	195	1.40
ACCIDENT 3	8298	6024	42.10
ACCIDENT 4	3778	10544	73.60

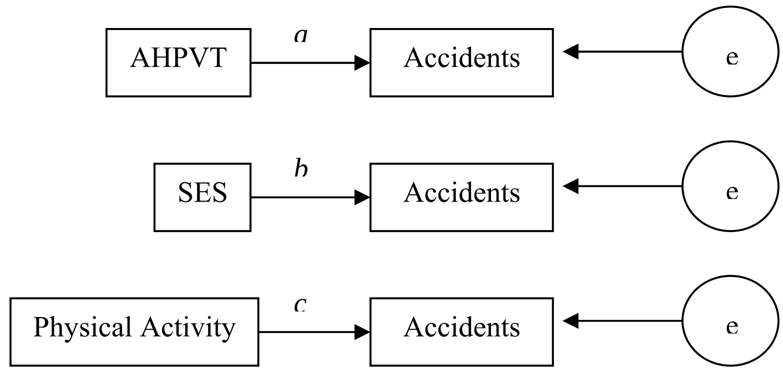

Figure 1. Path models regarding the predictive relationship between childhood intelligence and accidents, SES and accidents, and physical activity and accident incidence.

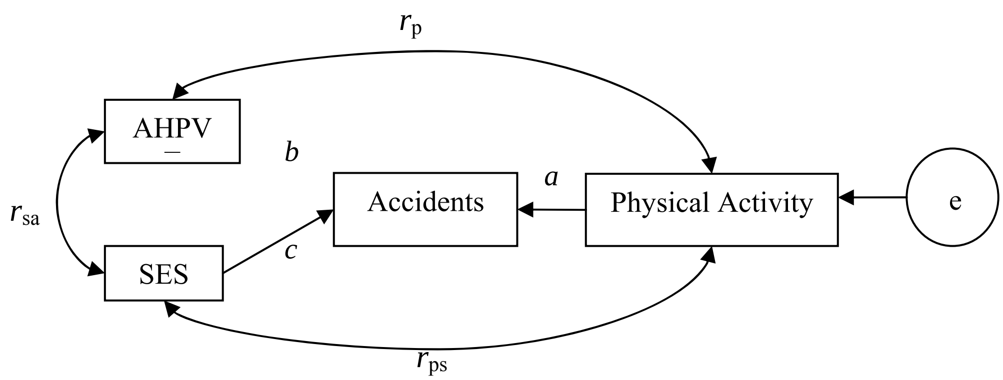

Figure 2. Path model using childhood intelligence to predict accident incidence, while controlling for physical activity and SES.

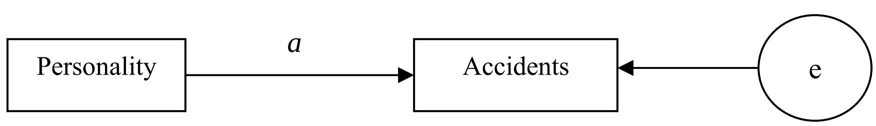

Figure 3. Path model using personality measures to predict accident incidence.

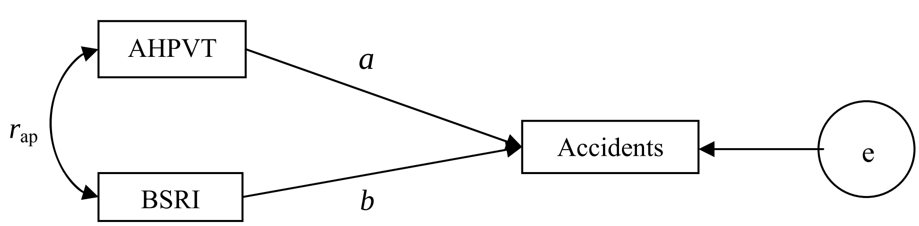

Figure 4. Path model using childhood intelligence and personality to predict accident incidence.

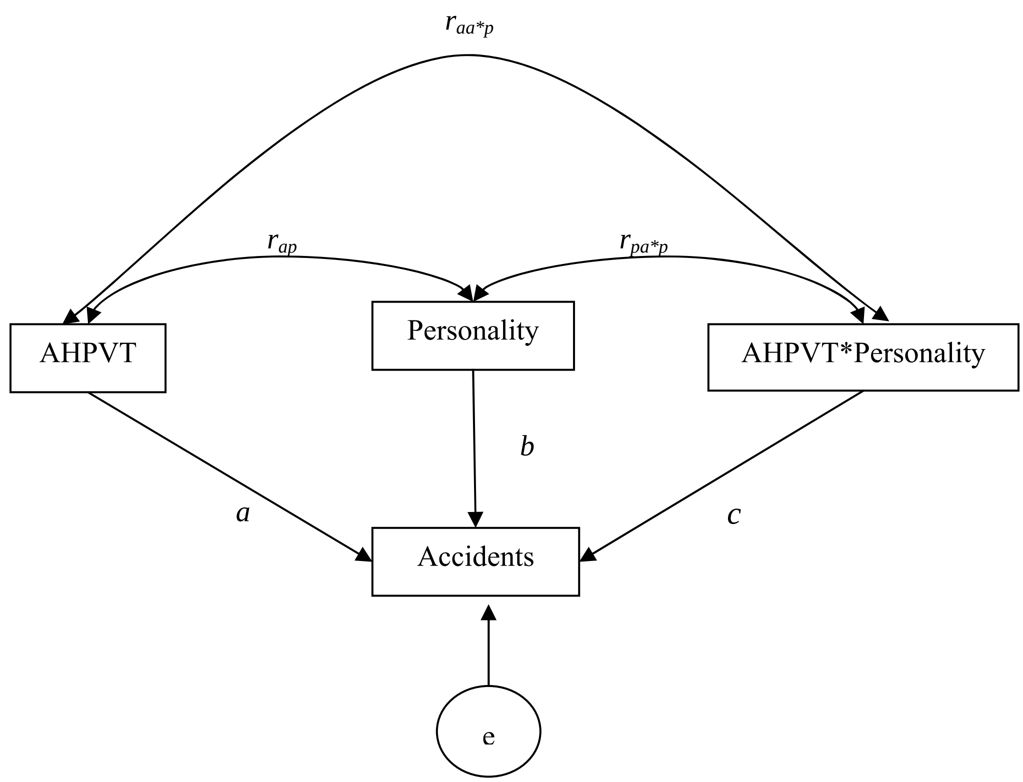

Figure 5. Path model using childhood intelligence to predict accident incidence with personality as a moderating variable.

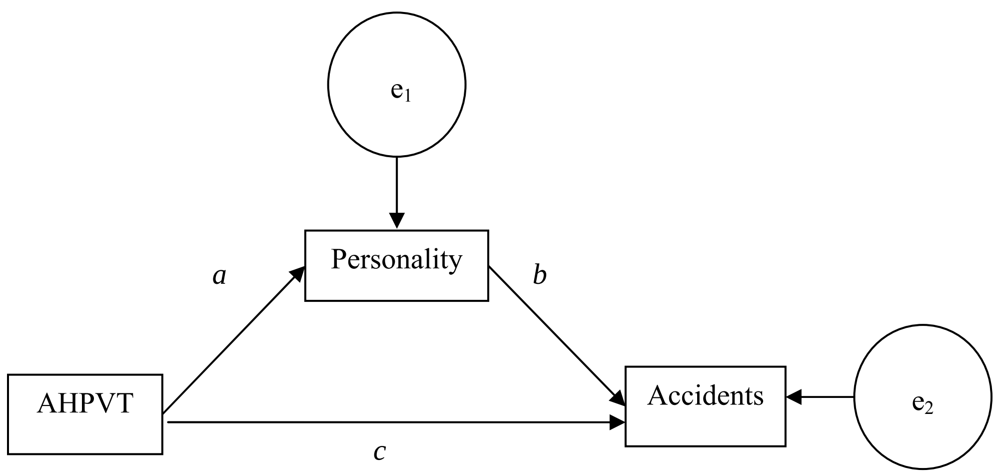

Figure 6. Path model using childhood intelligence to predict accidents with personality as a mediating variable.

Probit Model Regression

With probit regression

$$P\,(y = 1 \mid x) = \pi \mid x = \Phi\,(\beta_0 + \beta_1 x_1) \tag{1}$$

where π is defined as the probability of y = 1, and Φ is the cumulative standard normal distribution function (CSNDF). When the inverse is taken (Φ^{-1}), the model can be written as a linear regression equation:

$$\Phi^{-1}\,(\pi \mid x) = \beta_0 + \beta_1 x_1 \tag{2}$$

Latent Response Variable Formulation

The dichotomous outcome (accident or no accident in the present study) can be conceived as the result of an underlying non - observed (i.e., latent) continuous variable. If accident/no accident is the outcome variable (y), there exists an underlying continuous variable ($\breve{Y}$) where y = 1 if $\breve{Y}$ is larger than some threshold, τ, and 0 if it is less than the threshold. Consequently, this leads to the following:

$$Y = 1 \text{ if } \breve{Y} > \tau \text{ and } Y = 0 \text{ if } \breve{Y} \leq \tau\,. \tag{4}$$

A linear regression equation is used to relate $\breve{Y}$ to x,

$$\breve{Y} = \lambda x + \delta \tag{5}$$

Where λ is a slope parameter and δ is a residual that is uncorrelated with x. An intercept term is not needed because of the threshold parameter of, τ. Normality is assumed for the δ residual, $\delta \sim N(0, V(\delta))$. The latent response variable formulation results in the following model:

$$P(y = 1 \mid x) = Prob(\breve{Y} > \tau \mid x) = 1 - P(\breve{Y} \leq \tau \mid x) = 1 - \Phi[(\tau - \lambda x)V(\delta)^{-½}]. \tag{6}$$

where τ is the latent response variable threshold. Standardizing to $V(\delta) = 1$ defines a probit model with $\beta_0 = -\tau$ and $\beta_1 = \lambda$. The latent response variable formulation focuses on the linear relation between $\breve{Y}$ and x, as opposed to the non-linear relationship between the binary *y* variable and x. Nonetheless, the $\breve{Y}$ formulation can also be used to describe the resulting changes in probabilities of the binary *y*.

To describe these changes in the latent response variable $\breve{Y}$ as a function of x, it is convenient to consider a standardized form of the linear regression equation that relates $\breve{Y}$ to x, which is:

$$\lambda_{\text{standardized}} = \lambda * \text{s.d.}(x) / \text{s.d.}(\breve{Y}), \tag{7}$$

Where s.d. denotes the standard deviation and

$$\text{s.d.}(\breve{Y}) = \sqrt{\lambda^2 V(x) + V(\delta)}. \tag{8}$$

The resulting coefficient refers to a standard deviations change in $\breve{Y}$ for a λ -unit change in x from 0 to 1.

While an R^2 value is produced in the output of probit models, its value is different from an R^2 of Ordinary Least Squares *y* because the residual variance ($V(\delta)$) was set to a constant (1 in this analysis). When interpreting the explained variance, it should be noted that its values are usually considerably lower than the Ordinary Least Squares (OLR) R^2 values one would obtain for predicting continuous outcomes (Snijders & Boskers, 1999). Long (1997, section 4.3) provides an extensive overview of the various definitions for explained proportion variance (R^2) in logistic and probit model regressions.

Interpretation

To make interpretation easier, Risk Ratios(RR) were calculated for each model using the thresholds and probit coefficients (Moher, Cook, Eastwood, Olkin, Rennie, & Stroup, 2001; Zou, 2007). RR, also referred to as a relative risk, is a ratio of the probability of an event occurring in one group over another. The ratios range from zero to infinity, with 1.0 indicating equal risks.

CHAPTER FOUR

Analysis

In this chapter, I will provide the results of the analyses. The results are arranged according to the specific research questions that framed the analyses. The research questions are:

1. Does childhood intelligence predict accident incidence in early adulthood?
2. Does childhood intelligence predict accident incidence in early adulthood when controlling for childhood socioeconomic status and physical activity?
3. Does personality predict accident incidence in early adulthood?
4. How do particular personality traits influence the cognitive ability - accident incidence relationship?
    a. Do they add to the predictive ability?
    b. Do they moderate the relationship?
    c. Do they mediate the relationship?

Because accident incidence was measured using four different variables, each question requires four different analyses. The accident variables were dichotomous, so a latent variable probit regression model was used as the model for all analyses (See chapter 3 for more detail). All independent variables were mean - centered.

For each analysis, several things are reported that warrant brief explanations. First, while *p* values are reported, they are not of primary interest for determining the "significance" of an outcome. The reason is because the sample size is so large that extremely small and non-meaningful differences are found to be significantly different from zero, while not having any practical significance.

Practical significance is determined by Risk Ratios (RR; also referred to as Relative Risk). RR is the ratio of the probability of occurrence of an outcome among one group to another group. RRs are bounded at the lower end by zero, but unbounded at the upper end. RRs close to 1 mean that both groups have a similar probability of an outcome. For this study, RR ≈ 1 suggests that no meaningful difference exists in accident incidence between the two comparison groups. Only RRs above 2.50 and below .40 are considered "significant" and are interpreted as individuals being 2.50 times more likely to experience/not experience the outcome.(Let x = π_1 and y = π_2; If $\frac{\pi_1}{\pi_2}$ = 2.50, then $\frac{\pi_2}{\pi_1}$ = .40). Probit coefficients and thresholds were used to calculate RRs for individuals at 2 standard deviations above the mean vs. 2 standard deviations below the mean for the predictor variable(s) of interest. These two locations were chosen to compare individuals high on a trait versus those low on the trait.

In addition to RRs, the analysis can also be interpreted using the reported threshold and probit coefficients. The probit coefficients are equivalent to slopes in regression models and the threshold is the same as an intercept, except it has the opposite sign. For example, if the threshold is reported as .92, then the intercept would be -.92. The latent outcome variable, propensity for risk, is in the Z- metric (i.e., standardized normal distribution).

Finally, standardized thresholds (SDYX thresholds) and coefficients (SDYX coefficients) are reported. These can be interpreted similar to standardized variables in regular regression (i.e., as the predictor variable increases by a standard deviation the latent outcome variable increases by SDYX standard deviations.

Question One:Does Childhood Intelligence Predict Number of Accidents in Early Adulthood?

A simple regression was conducted, regressing each of the accident variables on intelligence (IQ), as measured by the ADPVT. The RRs range from 1.0 to 1.85 for each of the four models (see Table 17). This finding suggests that there is a negligible difference in accident occurrence between individuals with high and low cognitive ability.

Question Two:Does Childhood Intelligence Predict Accidents in Early Adulthood When Controlling for Childhood Socioeconomic Status (SES) and Physical Activity?

To answer this research question, multivariable regression was conducted. Before running the multivariate analysis, each of the covariates with IQ (SES and PA) were entered individually into simple regression models to test their association with the accident variables independently of the other covariates.

RRs for SES ranged from .45 to 1.04, while for PA they ranged from 2.01 to 4.20. This indicates that the effect of SES in predicting accidents is negligible. However, the results for PA suggest that individuals engaged in high amounts of physical activities were anywhere between 2 and 4 times more likely to have an accident than those with low physical activity; that is, the most active young adults were more likely to have an accident than the least active young adults. As previously shown, another way of conceptualizing these results, for Accident 1, is to say that individuals with an average PA score has a propensity for an accident, in the Z – score metric, of -.93 and that with every 1 unit of increase in PA, there would be a .20 increase in the propensity for accidents.

The multivariate probit regression modeled the relationship of all of the aforementioned independent variables (IQ, SES, and PA) with the accident variables. Holding SES and PA constant, IQ had no meaningful predictive relationship with any of the accident variables (RRs ranged from 1.00 to 1.56). SES, when IQ and PA were held constant, had no meaningful relationship with the accident variables (RRs ranged from .55 to 1.09). PA, when IQ and SES were held constant, demonstrated no meaningful relationship with any of the accident variables (RRs ranged from .32 to 1.77). Tables 11 through 14 show the results for the simple and multivariate models.

Question Three:Does Personality Predict Accidents in Early Adulthood?

To answer the question of whether personality predicts accidents in early adulthood, personality variables were put into a regression model to predict accidents. Each of the personality variables – Neuroticism (NEUROT), Extraversion (EXVSN), and Conscientiousness (CONSC) - were entered into a regression model independently. None of the variables were found to have any meaningful predictive relationship with the outcome variables. RRs ranged from .48 to .80 for NEUROT, .59 to .94 for EXVSN, and .80 to 1.10 for CONSC.

Two other variables, the BSRI masculinity (BemMale) and femininity (BemFem) scales, were used as proxies for personality variables in an exploratory, sub-sample analysis. In Wave III, only a sub-sample of individuals who were in relationship with members of the opposite sex were administered the BSRI. The two personality variables and corresponding IQ variables were entered into a regression model separately.

Table 11
Simple Regression of Intelligence on Accidents

Accident	Predictor	*n*	R^2	Threshold	Probit Coefficient	SDYX Threshold	SDYX Coefficient	RR	S.E.	*p*
1	IQ	14322	0.01	0.92	0.01	0.92	0.11	1.85	0.00	0.00
2	IQ	14322	0.00	0.94	0.00	0.94	-0.00	1.00	0.00	0.83
3	IQ	14322	0.02	0.05	0.01	0.05	0.15	1.21	0.00	0.00
4	IQ	14322	0.01	0.70	0.01	0.70	0.07	1.32	0.00	0.01

Note. IQ = intelligence; R^2 = Explained Variance; SDYX = Standardized thresholds and coefficients; RR= Risk Ratio; $p < .025$.

Table 12
Simple Regression of Socioeconomic Status on Accidents

Accident	Predictor	n	R^2	Threshold	Probit Coefficient	SDYX Threshold	SDYX Coefficient	RR	S.E.	*p*
1	SES	14322	0.02	0.93	-0.14	0.92	-0.14	0.45	0.04	0.00
2	SES	14322	0.00	0.94	0.01	0.94	0.01	1.04	0.02	0.77
3	SES	14322	0.01	0.05	-0.10	0.05	-0.10	0.71	0.02	0.00
4	SES	14322	0.00	0.70	-0.06	0.70	-0.06	0.75	0.03	0.05

Note. SES = Socioeconomic status; R^2 = Explained Variance; SDYX = Standardized thresholds and coefficients; RR= Risk Ratio; $p < .025$

Table 13
Simple Regression of Physical Activity on Accidents

Accident	Predictor	n	R^2	Threshold	Probit Coefficient	SDYX Threshold	SDYX Coefficient	RR	S.E.	*p*
1	PA	14322	0.04	0.93	0.20	0.92	0.19	3.30	0.03	0.00
2	PA	14322	0.02	0.95	0.13	0.94	0.12	2.11	0.02	0.00
3	PA	14322	0.04	0.05	0.21	0.05	0.20	2.01	0.02	0.00
4	PA	14322	0.07	0.72	0.27	0.69	0.26	4.20	0.03	0.00

Note. PA = Physical Activity; R^2 = Explained Variance; SDYX = Standardized thresholds and coefficients; RR= Risk Ratio; $p < .025$

Table 14
Multivariate Regression of Intelligence, Socioeconomic Status, and Physical Activity on Accidents

Accident	Predictor	n	R^2	Threshold	Probit Coefficient	SDYX Threshold	SDYX Coefficient	RR	S.E.	*p*
1	IQ	14322	0.06	0.94	0.01	0.91	0.08	1.56	0.02	0.03
	SES				-0.10		-0.10	0.55	0.04	0.01
	PA				0.20		0.19	0.41	0.03	0.00
2	IQ	14322	0.02	0.95	0.00	0.94	-0.01	1.00	0.00	0.81
	SES				0.01		0.01	1.09	0.02	0.50
	PA				0.13		0.12	0.32	0.02	0.00
3	IQ	14322	0.06	0.05	0.01	0.05	0.12	1.49	0.00	0.00
	SES				-0.05		-0.05	0.84	0.02	0.01
	PA				0.20		0.19	1.77	0.02	0.00
4	IQ	14322	0.07	0.72	0.00	0.69	0.06	1.37	0.00	0.04
	SES				-0.02		-0.02	0.92	0.03	0.56
	PA				0.27		0.26	0.76	0.03	0.00

Note. IQ = intelligence; SES = Socioeconomic status; PA = Physical Activity; R^2 = Explained Variance; SDYX = Standardized thresholds and coefficients; RR= Risk Ratio; $p < .02$.

The results indicate that the sub-sample confirmed findings from the other personality analyses; no simple predictive relationship exist. RRs for IQ ranged from 1.0 to 1.03; for BemMale, RRs ranged from .99 to 1.07; RRs for BemFemale ranged from .91 to .96. Tables 15 through 18 show the results of the analyses of the personality variables and results from the sub-sample analyses.

Question Four:How Do Particular Personality Traits Influence the Cognitive Ability - Accident Relationship?

Do They Add to the Predictive Ability?

A multivariate regression analyses was used to investigate whether personality traits add to the predictive ability of IQ on accident occurrence. Each accident variable was regressed on IQ and each individual personality trait separately. IQ, when CONSC was held constant, had no meaningful predictive relationship with any of the accident variables (RRs ranged from 1.00 to 1.85). CONSC, when IQ was held constant, had no meaningful predictive relationship with accidents (RRs ranged from .79 to 1.08). IQ, when EXVSN was held constant, had no meaningful predictive relationship with accidents (RRs ranged from 1.00 to 1.85). EXVSN, when IQ was held constant, had no meaningful predictive relationship (RRs ranged from .59 to .94). IQ, when NEUROT was held constant, had no meaningful predictive relationship with accidents (RRs ranged from 1.00 to 1.86). NEUROT, when IQ was held constant, had no meaningful predictive relationship with accidents (RRs ranged from .49 to .80).

In the sub-sample analysis, IQ, when BemMale was held constant, had a meaningful significant predictive relationship with Accident 4.

Table 15
Simple Regression of Conscientiousness on Accident Variables

Accident	Predictor	n	R^2	Threshold	Probit Coefficient	SDYX Threshold	SDYX Coefficient	RR	S.E.	*p*
1	CONSC	14322	0.00	0.92	0.02	0.92	0.02	1.10	0.03	0.59
2	CONSC	14322	0.00	0.94	0.01	0.94	0.01	1.07	0.02	0.52
3	CONSC	14322	0.00	0.06	0.01	0.06	0.01	1.04	0.02	0.49
4	CONSC	14322	0.00	0.70	-0.04	0.70	-0.04	0.80	0.03	0.09

Note. CONSC = Conscientiousness; R^2 = Explained Variance; SDYX = Standardized thresholds and coefficients; RR= Risk Ratio; $p < .025$

Table 16
Simple Regression of Extraversion on Accident Variables

Accident	Predictor	n	R^2	Threshold	Probit Coefficient	SDYX Threshold	SDYX Coefficient	RR	S.E.	*p*
1	EXVSN	14322	0.00	0.93	-0.06	0.93	-0.06	0.72	0.03	0.09
2	EXVSN	14322	0.00	0.94	-0.01	0.94	-0.01	0.94	0.02	0.61
3	EXVSN	14322	0.01	0.06	-0.07	0.06	-0.07	0.79	0.02	0.00
4	EXVSN	14322	0.01	0.71	-0.10	0.71	-0.10	0.59	0.03	0.00

Note. EXVSN = Extraversion; R^2 = Explained Variance; SDYX = Standardized thresholds and coefficients; RR= Risk Ratio; $p < .025$

Table 17
Simple Regression of Neuroticism on Accident Variables

Accident	Predictor	n	R^2	Threshold	Probit Coefficient	SDYX Threshold	SDYX Coefficient	RR	S.E.	*p*
1	NEUROT	14322	0.01	0.94	-0.10	0.93	-0.10	0.55	0.04	0.01
2	NEUROT	14322	0.00	0.95	-0.04	0.95	-0.04	0.80	0.02	0.02
3	NEUROT	14322	0.01	0.07	-0.08	0.07	-0.08	0.76	0.02	0.00
4	NEUROT	14322	0.02	0.73	-0.14	0.72	-0.13	0.49	0.03	0.00

Note. NEUROT = Neuroticism; R^2 = Explained Variance; SDYX = Standardized thresholds and coefficients; RR= Risk Ratio; $p < .025$

Table 18
Simple Regression of BSRI Masculinity and Femininity Scales on Accident Variables

Accident	Predictor	n	R^2	Threshold	Probit Coefficient	SDYX Threshold	SDYX Coefficient	RR	S.E.	*p*
1	IQ	3109	0.01	0.90	0.01	0.89	0.10	1.04	0.00	0.01
	Bemmale	972	0.00	1.03	-0.00	1.03	-0.01	0.99	0.01	0.83
	BemFemale	974	0.03	1.05	-0.02	1.03	-0.17	0.91	0.01	0.01
2	IQ	13007	0.00	0.94	0.00	0.94	-0.01	1.00	0.00	0.75
	Bemmale	3896	0.00	1.03	0.00	1.03	0.02	1.01	0.00	0.59
	BemFemale	3900	0.02	1.04	-0.01	1.02	-0.15	0.92	0.00	0.00
3	IQ	7673	0.02	-0.02	0.01	-0.02	0.14	1.03	0.00	0.00
	Bemmale	2345	0.01	0.10	0.02	0.10	0.08	1.03	0.00	0.01
	BemFemale	2349	0.02	0.10	-0.01	0.10	-0.13	0.96	0.00	0.00
4	IQ	3501	0.01	0.92	0.01	0.92	0.11	1.04	0.00	0.00
	Bemmale	1166	0.01	1.01	0.01	1.00	0.12	1.07	0.01	0.06
	BemFemale	1169	0.03	1.01	-0.02	0.99	-0.18	0.91	0.01	0.00

Note. IQ = Intelligence; BemMale = BSRI masculinity scale; BemFemale = BSRI femininity scale; R^2 = Explained Variance; SDYX = Standardized thresholds and coefficients; RR= Risk Ratio; $p < .025$.

The RR was 4.01, suggesting that individuals with higher IQ were 4 times more likely to be admitted to a hospital for and accident than those with lower IQ. There was no meaningful predictive relationship between IQ and the remaining accident variables, with the remaining RRs ranging from .91 to 1.85. BemMale, when IQ was held constant, had no meaningful predictive relationship with accidents. RRs ranged from .99 to 1.05. IQ, when BemFem was held constant, had substantial predictive relationships with Accident 3 and Accident 4. The RR for Accident 3 was 2.27, meaning that individuals with higher IQs were 2 times more likely to go to the emergency room as a result of an accident than those with lower IQ. The RR for Accident 4 was 7.71, meaning that individuals with higher IQ were 7 times more likely to be admitted to the hospital as a result of an accident. There was no meaningful predictive relationship between IQ and the remaining accident variables, with the remaining RRs ranging from 1.10 to 1.76. BemFem, when IQ was held constant, showed no meaningful predictive relationship with accidents. RRs ranged from .86 to .94. Tables 19 through 23 show the results from the multivariate probit regressions for IQ and CONSC, IQ and EXVSN, IQ and NEUROT, as well as the sub – sample analyses of IQ and BemMale and IQ and BemFem.

Does Personality Moderate the IQ - Accident Relationship?

A moderation effect occurs when the effect of a predictor variable on the outcome variable varies according to the level of a third variable, typically referred to as the *moderator variable* (Baron & Kenny, 1986; Beaujean, 2008; Cohen, 1978). In the current study, the moderation question asks: does personality moderate the IQ – accident relationship; that is, does the IQ – accident relationship change at different levels of personality?

Table 19

Multivariate Regression of Intelligence and Conscientiousness on Accident Variables

Accident	Predictor	n	R^2	Threshold	Probit Coefficient	SDYX Threshold	SDYX Coefficient	RR	S.E.	*p*
1	IQ	14322	0.01	0.92	0.01	0.91	0.11	1.85	0.00	0.00
	CONSC				0.01		0.01	1.08	0.03	0.69
2	IQ	14322	0.00	0.94	0.00	0.94	-0.01	1.00	0.00	0.81
	CONSC				0.01		0.01	1.07	0.02	0.51
3	IQ	14322	0.02	0.05	0.01	0.05	0.15	1.65	0.00	0.00
	CONSC				0.00		0.00	1.01	0.02	0.79
4	IQ	14322	0.01	0.70	0.01	0.70	0.08	1.47	0.00	0.01
	CONSC				-0.05		-0.05	0.79	0.03	0.07

Note. IQ = Intelligence; CONSC = Conscientiousness; R^2 = Explained Variance; SDYX = Standardized thresholds and coefficients; RR= Risk Ratio; $p< .025$.

Table 20
Multivariate Regression of Intelligence and Extraversion on Accidents Variables

Accident	Predictor	n	R^2	Threshold	Probit Coefficient	SDYX Threshold	SDYX Coefficient	RR	S.E.	*p*
1	IQ	14322	0.02	0.93	0.01	0.92	0.11	1.85	0.00	0.00
	EXVSN				-0.06		-0.06	0.71	0.02	0.01
2	IQ	14322	0.00	0.94	0.00	0.94	-0.00	1.00	0.00	0.83
	EXVSN				-0.01		-0.01	0.94	0.02	0.61
3	IQ	14322	0.03	0.06	0.01	0.06	0.15	1.66	0.00	0.00
	EXVSN				-0.07		-0.07	0.78	0.02	0.00
4	IQ	14322	0.02	0.71	0.01	0.71	0.08	1.48	0.00	0.01
	EXVSN				-0.10		-0.10	0.59	0.03	0.00

Note. IQ = Intelligence; EXVSN = Extraversion; R^2 = Explained Variance; SDYX = Standardized thresholds and coefficients; RR= Risk Ratio; $p < .025$.

Table 21

Multivariate Regression of Intelligence and Neuroticism on Accident Variables

Accident	Predictor	n	R^2	Threshold	Probit Coefficient	SDYX Threshold	SDYX Coefficient	RR	S.E.	*p*
1	IQ	14322	0.02	0.94	0.01	0.93	0.11	1.86	0.00	0.00
	NEUROT				-0.1		-0.1	0.56	0.04	0.01
2	IQ	14322	0.00	0.95	0.00	0.95	-0.01	1.00	0.00	0.80
	NEUROT				-0.04		-0.04	0.80	0.02	0.02
3	IQ	14322	0.03	0.07	0.01	0.06	0.15	1.66	0.00	0.00
	NEUROT				-0.08		-0.08	0.76	0.05	0.00
4	IQ	14322	0.02	0.73	0.01	0.72	0.07	1.48	0.00	0.02
	NEUROT				-0.14		-0.13	0.49	0.03	0.00

Note. IQ = Intelligence; NEUROT = Neuroticism; R^2 = Explained Variance; SDYX = Standardized thresholds and coefficients; RR= Risk Ratio; $p<$. 025

Table 22
Multivariate Regression of Intelligence and BSRI Masculinity Scale on Accident Variables

Accident	Predictor	n	R^2	Threshold	Probit Coefficient	SDYX Threshold	SDYX Coefficient	RR	S.E.	*p*
1	IQ	899	0.01	1.04	0.01	1.04	0.07	1.60	0.01	0.38
	BemMale				-0.00		-0.03	0.99	0.01	0.72
2	IQ	3620	0.00	1.02	-0.00	1.02	-0.02	0.91	0.00	0.60
	BemMale				0.00		0.01	1.01	0.00	0.81
3	IQ	2190	0.03	0.08	0.01	0.08	0.17	1.85	0.00	0.00
	BemMale				0.00		0.04	1.01	0.00	0.24
4	IQ	1084	0.06	1.02	0.02	0.99	0.21	4.01	0.00	0.00
	BemMale				0.01		0.09	1.05	0.01	0.19

Note. IQ = intelligence; BemMale = BSRI masculinity scale; R^2 = Explained Variance; SDYX = Standardized thresholds and coefficients; RR= Risk Ratio; $p< .025$.

Table 23
Multivariate Regression of Intelligence and BSRI Femininity Scale on Accident Variables

Accident	Predictor	n	R^2	Threshold	Probit Coefficient	SDYX Threshold	SDYX Coefficient	RR	S.E.	*p*
1	IQ	901	0.03	1.05	0.01	1.04	0.09	1.76	0.01	0.241
	BemFemale				-0.02		-0.16	0.91	0.01	0.011
2	IQ	3624	0.03	1.03	0.00	1.02	0.01	1.10	0.00	0.725
	BemFemale				-0.02		-0.17	0.91	0.00	0.000
3	IQ	2194	0.07	0.07	0.02	0.07	0.21	2.27	0.00	0.000
	BemFemale				-0.02		-0.18	0.94	0.00	0.000
4	IQ	1087	0.12	1.02	0.02	0.96	0.29	7.71	0.00	0.000
	BemFemale				-0.02		-0.26	0.86	0.01	0.000

Note. IQ = Intelligence; BemFemale = BSRI femininity scale; R^2 = Explained Variance; SDYX = Standardized thresholds and coefficients; RR= Risk Ratio; $p < .025$.

To investigate the possibility of a moderating relationship, regressions were run for each of the personality variables. IQ, at the average level of CONSC, had no meaningful predictive relationships with accidents (RRs range from .1.00 to1.85). IQ, at the average level of EXVSN, has no meaningful predictive relationship with accidents (RRs range from 1.00 to 1.65). IQ, at the average score on NEUROT, had no meaningful predictive relationships with accidents (RRs range from 1.00 to 1.86). Tables 24 through 26 show the results of the moderation effect on the predictive relationships between IQ and the personality variables.

In the sub-sample analysis, IQ, at the average level of BemMale, demonstrated a meaningful relationship with Accident 4. In that model, individuals with high IQ and an average score on BemMale were 4 times more likely to have an accident that required hospitalization. No other substantial predictive relationships exist between IQ and the remaining accident variables (RRs range from .91 to 1.85).

IQ, at the average level of BemFem, demonstrated a meaningful relationship with Accident 4 and a moderate relationship with Accident 3. In those models, individuals with high IQ and an average score on BemFem were 7 times more likely to have an accident that required hospitalization and 2 times more likely to have accidents that were treated in an emergency room. No other meaningful predictive relationships exist between IQ and the remaining accident variables (RRs range from 1.00 to 1.93). Tables 27 and 28 show the results of the moderation effect on the predictive relationships between IQ and the sub – sample personality variables.

Table 24
Moderation Effect on the Predictive Relationship Between Intelligence and Conscientiousness on Accident Variables

Accident	Predictor	n	R^2	Threshold	Probit Coefficient	SDYX Threshold	SDYX Coefficient	RR	S.E.	*p*
1	IQ	14322	0.01	0.92	0.01	0.91	0.11	1.85	0.00	0.00
	CONSC				0.01		0.01	1.08	0.03	0.64
	IQ*CONSC				0.00		0.00		0.00	0.84
2	IQ	14322	0.00	0.94	0.00	0.94	-0.00	1.00	0.00	0.80
	CONSC				0.01		0.01	1.08	0.02	0.49
	IQ*CONSC				0.00		0.02		0.00	.20
3	IQ	14322	0.02	0.05	0.01	0.05	0.15	1.65	0.00	0.00
	CONSC				0.01		0.01	1.02	0.02	0.76
	IQ*CONSC				0.00		0.02		0.00	0.32
4	IQ	14322	0.01	0.70	0.01	0.70	0.07	1.47	0.00	0.01
	CONSC				-0.05		-0.05	0.79	0.03	0.07
	IQ*CONSC				-0.00		-0.02		0.00	0.32

Note. IQ = Intelligence; CONSC = Conscientiousness; IQ*CONSC = Interaction term; R^2 = Explained Variance; SDYX = Standardized thresholds and coefficients; RR= Risk Ratio; $p< .025$

Table 25
Moderation Effect on the Predictive Relationship Between Intelligence and Extraversion on Accident Variables

Accident	Predictor	n	R^2	Threshold	Probit Coefficient	SDYX Threshold	SDYX Coefficient	RR	S.E.	*p*
1	IQ	14322	0.02	0.93	0.01	0.92	0.12	2.03	0.00	0.00
	EXVSN				-0.07		-0.07	0.66	0.02	0.00
	IQ*EXVSN				0.00		0.06		0.00	0.14
2	IQ	14322	0.00	0.94	0.00	0.94	-0.01	1.00	0.00	0.81
	EXVSN				-0.01		-0.01	0.94	0.02	0.65
	IQ*EXVSN				0.00		-0.01		0.00	0.80
3	IQ	14322	0.03	0.06	0.01	0.06	0.15	1.65	0.00	0.00
	EXVSN				-0.07		-0.07	0.79	0.02	0.00
	IQ*EXVSN				-0.00		-0.02		0.00	0.35
4	IQ	14322	0.02	0.71	0.01	0.71	0.08	1.48	0.00	0.01
	EXVSN				-0.10		-0.10	0.59	0.03	0.00
	IQ*EXVSN				0.00		0.01		0.00	0.90

Note. IQ = Intelligence; EXVSN = Extraversion; IQ*EXVSN = Interaction term; R^2 = Explained Variance; SDYX = Standardized thresholds and coefficients; RR= Risk Ratio; $p < .025$

Table 26
Moderation Effect on the Predictive Relationship Between Intelligence and Neuroticism on Accident Variables

Accident	Predictor	n	R^2	Threshold	Probit Coefficient	SDYX Threshold	SDYX Coefficient	RR	S.E.	*p*
1	IQ	14322	0.02	0.94	0.01	0.93	0.11	1.86	0.00	0.00
	NEUROT				-0.10		-0.10	0.56	0.04	0.01
	IQ*NEUROT				-0.00		-0.01		0.00	0.59
2	IQ	14322	0.00	0.95	0.00	0.95	-0.01	1.00	0.00	0.75
	NEUROT				-0.04		-0.04	0.80	0.02	0.02
	IQ*NEUROT				0.00		-0.01		0.00	0.70
3	IQ	14322	0.03	0.06	0.01	0.06	0.14	1.58	0.00	0.00
	NEUROT				-0.08		-0.08	0.76	0.02	0.00
	IQ*NEUROT				-0.00		-0.03		0.00	0.16
4	IQ	14322	0.02	0.73	0.00	0.72	0.07	1.37	0.00	0.03
	NEUROT				-0.14		-0.13	0.49	0.03	0.00
	IQ*NEUROT				-0.00		-0.02		0.00	0.38

Note. IQ = intelligence; NEUROT = Neuroticism; IQ*NEUROT = Interaction term; R^2 = Explained Variance; SDYX = Standardized thresholds and coefficients; RR= Risk Ratio; *p*< .025.

Table 27
Moderation Effect on the Predictive Relationship Between Intelligence and the BSRI Masculinity Scale on Accident Variables

Accident	Predictor	n	R^2	Threshold	Probit Coefficient	SDYX Threshold	SDYX Coefficient	RR	S.E.	*p*
1	IQ	899	0.01	1.06	0.01	1.05	0.07	1.60	0.01	0.37
	BemMale				-0.00		-0.01	0.99	0.01	0.86
	IQ*BemMale				0.00		0.07		0.00	0.45
2	IQ	3620	0.00	1.02	-0.00	1.02	-0.02	0.91	0.00	0.59
	BemMale				0.00		0.00	1.00	0.00	0.91
	IQ*BemMale				0.00		-0.02		0.00	0.63
3	IQ	2190	0.04	0.09	0.01	0.09	0.17	1.85	0.00	0.00
	BemMale				0.01		0.06	1.02	0.00	0.12
	IQ*BemMale				0.00		0.05		0.00	0.11
4	IQ	1084	0.07	1.06	0.02	1.02	0.21	4.54	0.00	0.00
	BemMale				0.02		0.16	1.10	0.01	0.06
	IQ*BemMale				0.00		0.18		0.00	0.01

Note. IQ = intelligence; BemMale = BSRI masculinity scale; IQ*BemMale = Interaction term; R^2 = Explained Variance; SDYX = Standardized thresholds and coefficients; RR= Risk Ratio; *p*< .025.

Table 28

Moderation Effect on the Predictive Relationship Between Intelligence and BSRI Femininity Scale on Accident Variables

Accident	Predictor	n	R^2	Threshold	Probit Coefficient	SDYX Threshold	SDYX Coefficient	RR	S.E.	*p*
1	IQ	901	0.03	1.06	0.01	1.04	0.10	1.93	0.01	0.25
	BemFemale				-0.01		-0.16	0.92	0.01	0.02
	IQ*BemFemale				0.00		0.03		0.00	0.75
2	IQ	3624	0.03	1.03	0.00	1.01	0.00	1.00	0.00	0.93
	BemFemale				-0.02		-0.18	0.90	0.00	0.00
	IQ*BemFemale				0.00		-0.05		0.00	0.21
3	IQ	2194	0.07	0.06	0.02	0.06	0.21	2.14	0.00	0.00
	BemFemale				-0.02		-0.20	0.94	0.00	0.00
	IQ*BemFemale				0.00		-0.05		0.00	0.10
4	IQ	1087	0.12	1.01	0.02	0.95	0.29	7.67	0.01	0.00
	BemFemale				-0.03		-0.27	0.86	0.01	0.00
	IQ*BemFemale				0.00		-0.03		0.00	0.68

Note. IQ = intelligence; BemFemale = BSRI femininity scale; IQ*BemFemale = Interaction term; R^2 = Explained Variance; SDYX = Standardized thresholds and coefficients; RR= Risk Ratio; $p < .025$.

Does Personality Mediate the IQ - Accident Relationship?

Mediation is when the effect of one variable on another variable is transmitted through a third variable, referred as the *mediator variable* (MacKinnon, 2008; Shrout & Bolger, 2002). In order to have a mediating relationship, three basic criteria must be met: (1) the predictor variable must be related to the outcome, (2) the mediator variable must be related to the outcome, and (3) the predictor variable must predict the mediator variable (Beaujean, 2008). In the present study, IQ (the predictor) did not, by itself, predict accidents (outcome variable) and most of the personality variables (mediator variables) did not have an interpretable relationship with accidents (outcome variable). Since all three of the criteria needed for mediation to possibly exist, this analysis was not conducted.

CHAPTER FIVE

Conclusion

In this chapter, I will provide a brief summary of the sample used in the current study, the research questions and results, and a discussion of the findings. I will also provide limitations to the current study and direction for future research. The chapter will conclude with a brief summary of the current study.

Summary of Sample

The current study used data from the National Longitudinal Study of Adolescent Health (Add Health; for more on its research design, see Udry & Bearman, 1998). The Add Health study was initiated in 1994 under a grant from the National Institute of Child Health and Human Development (NICHD) with co-funding from 17 other federal agencies. It is designed to be the largest, most comprehensive survey of adolescents ever undertaken to study the health related behaviors of adolescent male and females, grades 7 through 12, and their outcomes in young adulthood. The first wave (Wave I) of data collection was conducted in two stages between September 1994 and December 1995. In 2001 and 2002, Add Health respondents, now 18 to 26 years old, were re-interviewed (Wave III) to investigate the health status of the sample in young adulthood. Data from Wave I and Wave III are used in the current study. There were 14, 322 students that had data from both Wave I and Wave III that were used for this study.

Research Questions and Summary of Results

In this study, the relationship between childhood intelligence (IQ), personality, and accidents in early adulthood was investigated. Specifically, this study sought to answer the following research questions:

1. Does childhood intelligence predict accident incidence in early adulthood?
2. Does childhood intelligence predict accident incidence in early adulthood when controlling for childhood socioeconomic status and physical activity?
3. Does personality predict accident incidence in early adulthood?
4. How do particular personality traits influence the cognitive ability - accident incidence relationship?
    a. Do they add to the predictive ability?
    b. Do they moderate the relationship?
    c. Do they mediate the relationship?

The findings from the analyses are:

1. Childhood intelligence, by itself, is not a meaningful predictor of accident incidence in early adulthood.
2. Childhood intelligence is not a meaningful predictor of accident incidence in early adulthood after controlling for childhood socioeconomic status (SES) and physical activity (PA). However, physical activity does have a meaningful predictive relationship with all four of the accident variables.
3. Personality traits - specifically Conscientiousness, Extraversion, and Neuroticism – do not, by themselves, have a meaningful predictive relationship with accident incidence in early adulthood. This finding holds in a sub – sample analysis,

which used the Bem Sex Role Inventory (BSRI; Bem, 1974) masculinity (BemMale) and femininity (BemFemale) scales as proxies for composite personality variables.

4. There was no evidence suggesting that personality had any meaningful influence on the intelligence – accident incidence relationship. Sub – sample analyses using the BSRI masculinity and femininity scales did find occurrences in which the relationship was influenced (Accident 3), but this single relationship, however, did not fit into any interpretable pattern.
    a. Personality measures did not add to the predictive relationship between childhood intelligence and accident incidence in early adulthood. The one caveat is in the aforementioned sub – sample analyses using the BSRI masculinity and femininity scales.
    b. Personality measures did not demonstrate any moderating effect on the childhood intelligence and accident incidence in early adulthood relationship.
    c. The basic criteria for a mediation relationship to exist were not met, so this analysis was not conducted.

Discussion

In the field of cognitive epidemiology (CE; Deary & Batty, 2007), it has been well established that intelligence is a consistent predictor of a variety of health outcomes, such as mortality (Batty, Deary, & Gottfredson, 2007; Hart et al., 2005; Kuh, Richards, Hardy, Butterworth, & Wadsworth, 2004), heart disease (Hemmingson, Melin, Allebeck,

& Lundberg, 2006), and dementia (Snowdon, Kemper, Mortimer, Greiner, Wekstein, & Markesbery, 1996) in middle and late adulthood.

Personality traits have been found to enhance the predictive ability in important life outcomes such as job performance (Dunn, Mount, & Barrick, 1995; Ones, Viswesvaran, & Schmidt, 1993; Schmidt & Hunter, 2004), occupational level and income (Judge, Higgins, Thorensen, & Barrick, 1999), and health outcomes (Schwartz, Friedman, Tucker, Tomlinson-Keasey, Wingard, & Criqui, 1995). Personality traits have also been found to predict life outcomes such as mortality, divorce, and occupational outcomes better than other potential causes, such as socioeconomics (Roberts, Kuncel, Shiner, Caspi, & Goldberg, 2007). These findings, in addition to research suggesting personality trait measures stand as one of the two primary construct domains that account for much of the differences between individuals (Austin et al., 2002), provide the basis for this current investigation.

The current investigation into the predictive relationship between individual differences and accident incidence in early adulthood yielded a pattern that was inconsistent with the extant literature within the field of CE (Deary & Batty, 2007) based upon the *a priori* level of practical significance set by the researcher. In models where IQ was predictive of accidents, there were no systematic patterns as to why the relationship might exist. Therefore, caution is in order when interpreting the anomalous results, due to possibility of it being a chance occurrence (Lord, Gebski, & Keech, 2004). For the clear majority of the models, neither of the predictor variables of interest demonstrated meaningful relationships with accidents in early adulthood.

There are at least three possible reasons for the lack of meaningful predictive relationships in the current study. First, it could be that no relationship actually exists between IQ, personality, and accidents. As previously mentioned, this runs contrary to the bulk of the literature in the field of cognitive epidemiology (CE). Most CE investigators use large, longitudinal data sets, and have demonstrated that childhood IQ is a strong predictor of various health outcomes in middle and late adulthood (Batty, Deary, & Gottfredson, 2006; Hart et al., 2005; Hemmingson, Melin, Allebeck, & Lundberg, 2006; Kuh, Richards, Hardy, Butterworth, & Wadsworth, 2004), independent of potentially confounding environmental factors such as childhood social position (Martin & Kubzansky, 2005; Silventoinen, Modig-Wennerstad, Tynelius, & Rasmussen, 2007) and despite the various types of tests to used to measure cognitive ability (Batty et al., 2007). This includes injuries and mortality attributed to assorted types of accidents (Lawlor, Clark, & Leon, 2007; O'Toole, 1990).

Likewise, as previously mentioned, personality traits have been found to enhance predictive ability in important health outcomes (Schwartz, Friedman, Tucker, et al., 1995), as well as predict some health outcomes better than much used predictors such as SES (Roberts, Kuncel, Shiner, Caspi, & Goldberg, 2007). Of specific interest for the current study, personality has been found to enhance the predictive ability of accident involvement in both occupational and non-occupational settings (Clark & Robertson, 2005; Sümer, Lajunen, & Özkan, 2005).

The accident literature has clearly established that accidents are not random occurrences, but that some individuals have more accidents than others. This finding holds even when the level of exposure to the same hazards in the same environment exist

(Boyle, 1980; Hale & Glendon, 1987, pp. 314–316). While constraints have made it difficult to parse out which individual differences are most pertinent for accident prevention, accident research has demonstrated that the risk of accidents is higher among workers who have less experience in the task at hand or when tasks are more complex (Boyle, 1980; Hale & Hale, 1972) - a pattern similar to the relationship with intelligence and job performance. The more complex the problem, the more *g*, or mental competence, is needed (Gottfredson, 2004a).

A second possibility for the lack of meaningful predictive relationships between individual differences and accidents may be due to the fact that the dependent variable may be measuring something in addition to just accidents in early adulthood. For example, it is possible that the dependent variables may be measuring healthcare choices as opposed to accident incidence. Each of the dependent variables entered into the various regressions were closely related to healthcare choices (e.g., did not get medical attention, reason for last visit to doctor, reason for ER visit, reason for last hospital stay). If this is the case, then other confounding factors, besides intelligence and personality, may contribute to the outcome; such as whether a respondent had insurance, availability of healthcare facilities, etc. However, this possibility is limited by the fact that the physical activity variable demonstrated a meaningful relationship with all four accident variables in the current study, and that there is a substantial body of existing literature documenting the relationship of sports and physical activities to accidental injuries (Bahr & Krosshaug, 2005; Matilla, Parkkari, Kannus, & Rimpelä, 2004; Mo, Turner, Krewski, & Merrick, 2006).

A third possibility for the lack of predictive relationship between individual differences and accidents in early adulthood is that maybe none exist in early adulthood, but begin to show up in middle and later adulthood, when life experiences have more time to accumulate and become more varied. In other words, accidents in early adulthood may be influenced by factors other than intelligence and personality, and their predictive relationship may not be detectable until later adulthood. This hypothesis finds support from Gordon's (1997; Gottfredson, 2003) conceptualization of life as mental battery containing multiple subtests with a wide range of *g* – loadings. As such, it could be that in early adulthood, accidents as a test of intelligence may not be heavily *g* – loaded because other factors, such as physical activity (the strongest predictor of accidents in the current study), confound the results.

Physical activities may be part of life style choices that people with multiple intellectual and/or personality constellations have, but how one remains safe while participating in healthy activities may not be a discriminating factor in early adulthood, as young adults are more physically active than any other time in adulthood. As one grows older, however, they might recognize the toll accidents and injuries have on their body and work to prevent future occurrences. Another way of expressing this is, as one gets older and accumulates more life experiences, the *g* – loading on this particular life subtest may increase because more intelligent individuals, who may also be more conscientious or open in their personality, will continue with a healthy lifestyle, albeit in a more careful and thoughtful manner. This is definitely an area for future research.

Limitations

One of the largest limitations in the current study has to do with the outcome variable. The accident variable in the current study does not provide the best measure of accident incidence in early adulthood. While it does provide an indicator of accident occurrence, there is the possibility that it is a better indicator of healthcare choice. A better measure of accidents would have been a variable that more clearly distinguishes the type and severity of accident, or variables that asked specifically about accident occurrence and reasons for accidents. As with many retrospective studies, the researchers are limited to the variables at hand. Given this reality, the accident variables selected for the current study provided the best possible measures of accidents in early adulthood in the Add Health data.

A second limitation, closely related to the first, are the measures of personality used in this study. Ideally, the current study could have been enhanced had actual, standardized personality measures been collected from the Add Health sample. Instead, personality measures were constructed by mapping personality-type questions from the In-Home survey on to a standardized measure of personality, and using a measure of sex roles (BSRI) that has been found to demonstrate strong correlations with standardized personality measures (Lippa, 1991; 1995; 2001).

Finally, the study may have been strengthened if the Bem Sex Role Inventory (BSRI) was administered to the entire Add Health sample. Having 14, 322 cases to analyze, as opposed to the smaller, sub-sample *n*, might have provided a better estimate of the true effects.

Future Research

There are several areas to be considered for future research. One such area would be to further investigate the relationship of multiple personality traits and IQ on health outcomes. The largest predictive relationships involving childhood intelligence and accidents in early adulthood occurred in the regressions including the masculinity and femininity scales of the Bem Sex Role Inventory (BSRI; Bem, 1974). These measures are composite personality variables and it may be that the constructs they measure contributed to the increased predictive relationship.

Another potential area for future research is the investigation of the relationship between physical activities and accidents; specifically, if or how this relationship may change over time. If life really can be conceived as an IQ test (Gordon, 1997; Gottfredson, 2003), then one might expect the strength of the predictive relationship between physical activity and accidents to change over time; specifically, one might find that the PA – accident relationship increases and IQ may play more of a mediating or moderating role in the relationship.

Finally, it would be beneficial for future research to investigate potentially changing relationships between the predictor variables used in the current study and later waves in the Add Health study. This would allow researchers to investigate whether the individual difference – accident relationship changes with age; that is, as the Add Health population grows older, does the predictive strength of IQ and/or personality get stronger. This, too, would investigate the hypothesis put forth by Gordon (1997) and Gottfredson (2003).

Summary

The current study sought to investigate if individual differences could predict accidents in early adulthood. Utilizing a measure of childhood intelligence, several constructed measures of personality, and two possible covariates (childhood socioeconomic status and physical activity), this study found that in early adulthood, neither IQ nor any of the personality measures had any meaningful predictive relationship with accidents. Physical activity was the only variable to consistently demonstrate meaningful predictive relationships with all four measures of accidents, and may warrant future research in the IQ field.

Finally, in a sub-sample analysis using masculinity (BemMale) and femininity (BemFemale) scales from the short form of the Bem Sex Role Inventory (BSRI; Bem, 1974) as proxies for personality, IQ demonstrated a meaningful predictive relationship to accident incidence, as determined by the respondent being treated in an emergency room for treatment, when analyzed in conjunction with the two scales from the Bem Sex Role Inventory. This single relationship, however, did not fit into any interpretable pattern. As such, it may be that this is simply an anomalous finding or it may have to do with the composite personality traits that each scale measured. As such, this becomes an area for consideration in future research.

APPENDICES

APPENDIX A

Add Health Questions Used to Form Study Variables

This appendix includes several tables showing questions from the Add Health data and the variables they formed, which were used in the current study.

A1
Add Health Variables Mapped Onto NEO-PI-R Conscientiousness Scale Questions

NEO-PI-R	Add Health		
Question	Question	Questionnaire	Section
Pay attention to details.	(H1PF21) After carrying out a solution to a problem, you usually try to analyze what went right and what went wrong.	In-Home Questionnaire (Wave I)	Personality and Family
Do things according to a plan.	(H1PF18) When you have a problem to solve, one of the first things you do is get as many facts about the problem as possible.	In-Home Questionnaire (Wave I)	Personality and Family
	(H1PF19) When you are attempting to find a solution to a problem, you usually try to think of as many different ways to approach the problem as possible.	In-Home Questionnaire (Wave I)	Personality and Family
	(H1PF20) When making decisions, you generally use a systematic method for judging and comparing alternatives.	In-Home Questionnaire (Wave I)	Personality and Family
Am exacting in my work.	(H1PF8) When you get what you want, it's usually because you worked hard for it	In-Home Questionnaire (Wave I)	Personality and Family
Shirk my duties.	(H1PF14) You usually go out of your way to avoid having to deal with problems in your life.	In-Home Questionnaire (Wave I)	Personality and Family

A2

Add Health Variables Mapped Onto NEO-PI-R Extraversion Scale Questions

NEO-PI-R	Add Health		
Question	Question	Questionnaire	Section
Feel comfortable around people.	(H1PF35) You feel socially accepted.	In-Home Questionnaire (Wave I)	Personality and Family
Make friends easily	(H1NB1) You know most of the people in your neighborhood	In-Home Questionnaire (Wave I)	Neighborhood
	(S62B) How strongly do you agree or disagree with the following statements? I feel close to people at school.	In-School Questionnaire (Wave I)	
	(S62E) I feel like I am a part of this school.	In-School Questionnaire (Wave I)	
	(S62O) I feel socially accepted.	In-School Questionnaire (Wave I)	
Am skilled in handling social situations.	(S44A32) Darken the oval if you are participating in student council this year, or if you plan to participate in it later in the school year (paraphrased).	In-School Questionnaire (Wave I)	
Don't mind being the center of attention.	(H1DS15) In the last 12 months, how often did you act loud, rowdy, or unruly in a public place?	In-Home Questionnaire (Wave I)	Delinquency Scale

A3

Add Health Variables Mapped Onto NEO-PI-R Neuroticism Scale Questions

NEO-PI-R	Add Health		
Question	Question	Questionnaire	Section
Seldom feel blue.	(H1PF10) You never get sad.	In-Home Questionnaire (Wave I)	Personality and Family
Feel comfortable with myself.	(H1PF36) You feel loved and wanted.	In-Home Questionnaire (Wave I)	Personality and Family
Am very pleased with myself.	(H1PF 30) You have a lot of good qualities	In-Home Questionnaire (Wave I)	Personality and Family

(table continues)

NEO-PI-R	Add Health		
Question	Question	Questionnaire	Section
	(H1PF 32) You have a lot to be proud of.	In-Home Questionnaire (Wave I)	Personality and Family
	(H1PF33) You like yourself just the way you are.	In-Home Questionnaire (Wave I)	Personality and Family
	(H1PF34) You feel like you are doing everything just about right	In-Home Questionnaire (Wave I)	Personality and Family

A4
Add Health Questions Used for Childhood Socioeconomic Status Variable

Question	Questionnaire Form	Section
(PA55) About how much total income, before taxes, did your family receive in 1994?	Parent In-Home Questionnaire (Wave I)	Section A: Core
(PA57) Last month, did you or any member of your household receive:	Parent In-Home Questionnaire (Wave I)	Section A: Core
(B) Supplemental Security Income (SSI)?		
(C) Aid to Families with Dependent Children (AFDC)?		
(D) Food stamps?		
(F) A housing subsidy or public housing?		

A5
Add Health Questions Used for Physical Activity Variable

Question	Questionnaire	Section
(H3DA8) In the past seven days, how many times did you bicycle, skateboard, dance, hike, hunt, or do yard work?	IHQ (WIII)	DA
(H3DA9) In the past seven days, how many times did you roller blade, roller skate, downhill ski, snow board, play racquet sports, or do aerobics?	IHQ (WIII)	DA
(H3DA10) In the past seven days, how many times did you participate in strenuous team sports such as football, soccer, basketball, lacrosse, rugby, field hockey, or ice hockey?	IHQ (WIII)	DA

(table continues)

Question	Questionnaire	Section
(H3DA11) In the past seven days, how many times did you participate in individual sports such as running, wrestling, swimming, cross-country skiing, cycle racing, or martial arts?	IHQ (WIII)	DA
(H3DA12) In the past seven days, how many times did you participate in gymnastics, weight lifting, or strength training?	IHQ (WIII)	DA
(H3DA13) In the past seven days, how many times did you play golf, go fishing or bowling, or play softball or baseball?	IHQ (WIII)	DA

Note. IHQ (WIII) = In –Home Questionnaire (Wave III); DA = Daily Activities

A6
Add Health Questions Used for Accident Variables

Variable	Questionnaire	Section
ACCIDENT 1		
Has there been any time in the past 12 months when you thought you should get medical care, but you did not? What type of problems were you having at that time? (H3HS7D) were injured by accident (1 = Accident)	In - Home Survey (Wave III)	Access to Health Services, Health Insurance
ACCIDENT 2		
(H3HS12) What was the main reason you went to the doctor or nurse? (1 = Accident)	In - Home Survey (Wave III)	Access to Health Services, Health Insurance
ACCIDENT 3		
(H3ID28) What was the main reason for your most recent emergency room visit? (1 = Accident)	In - Home Survey (Wave III)	Illnesses, Medications, and Physical Disabilities
ACCIDENT 4		
(H3ID31) What was the main reason for this hospitalization? (1 = Accident)	In - Home Survey (Wave III)	Illnesses, Medications, and Physical Disabilities

APPENDIX B

Mplus Syntax

Appendix B includes Mplus syntax used to run the analyses used in the current study.   Mplus software and documentation can be obtained from http://www.statmodel.com/

```
DATA:
FILE IS midatasets2.dat;
TYPE = IMPUTATION;
VARIABLE: NAMES ARE
PSUSCID REGION GSWGT3_2 H3HS7D H3HS12 H3ID28 H3ID31 PRNT_SES
activity PPVT_IQC EXVSN_1C PVT_EXV1 NEUROTC PVT_NEUR CON_C
PVT_CONS bemml_c  PVT_bmMC bemfml_c PVT_bmFC MULT OBS;! take out last
two variables for mediation and bem;
MISSING ARE .;
CLUSTER = psuscid;
WEIGHT = GSWGT3_2;
STRATIFICATION = REGION;
!CATEGORICAL IS H3HS7D;!accidents 1
!CATEGORICAL IS H3HS12;!accidents 2
!CATEGORICAL IS H3ID28;!accidents 3
CATEGORICAL IS H3ID31;!accidents 4

!IQ, SES, REGRESSIONS
USEVARIABLES H3ID31 PPVT_IQC; !Model 1
!USEVARIABLES H3ID31 PRNT_SES; !Model 2
!USEVARIABLES H3ID31 activity; !model 4
!USEVARIABLES H3HS12 PPVT_IQC PRNT_SES activity; !model 5
!PERSONALITY REGRESSIONS

!USEVARIABLES H3ID28 EXVSN_1C; !model 1
!USEVARIABLES H3ID28 NEUROTC; !model 3
!USEVARIABLES H3ID31 CON_C; !model 4

!personality and IQ
!USEVARIABLES H3ID31 PPVT_IQC EXVSN_1C; !EXTRAVERSION_1 IQ
!USEVARIABLES H3ID31 PPVT_IQC NEUROTC; !NEUROTC IQ
!USEVARIABLES H3ID31 PPVT_IQC CON_C; !CON_C IQ
```

```
!Moderation models
!Means
!PPVT_IQC: 100.890
!EXVSN_1C: .106
!EXVSN_2: -.129
!NEUROTC: .147
!CON_C: .060
!BEMMALE: 48.121
!BEMFMLE: 56.340

!USEVARIABLES H3ID31 PVT_EXV1 PPVT_IQC EXVSN_1C ; !Moderation 1
!USEVARIABLES  H3ID31 PPVT_IQC  NEUROTC PVT_NEUR ;!Moderation 3
!USEVARIABLES  H3ID31 PPVT_IQC CON_C PVT_CONS; !Moderation
!bem Analyses
!USEVARIABLES H3ID31 PPVT_IQC; !Regression IQ
!USEVARIABLES H3ID31 bemml_c  ; !Regression bemmale
!USEVARIABLES H3ID31 bemfml_c  ; !Regression bemfemale

!USEVARIABLES H3ID31 PPVT_IQC bemml_c ; !does IQ and bemmale predict
!accidents ?
!USEVARIABLES H3ID31 PPVT_IQC bemfml_c  ; !does IQ and  bemfemale predict
!accidents ?
!USEVARIABLES H3ID31 bemml_c  PPVT_IQC !Mediation 1
!USEVARIABLES H3ID31 bemfml_c  PPVT_IQC !Mediation 2

!USEVARIABLES  H3ID31 PPVT_IQC bemml_c PVT_bmMC; !Moderation
!USEVARIABLES  H3HS12 PPVT_IQC bemfml_c PVT_bmFC; !Moderation
!MODEL:

H3ID31 ON PPVT_IQC; ! does IQ predict accidents?
!H3ID31 ON PRNT_SES; !does Parent SES predict accidents?
!H3ID31 ON activity; !does activity predict accidents?
!H3HS12 ON PPVT_IQC PRNT_SES activity; !does IQ predict accidents with
!covariates in model?
```

```
!H3ID28 ON EXVSN_1C; !does extraversion predict accidents ?
!H3ID31 ON NEUROTC; !does neuroticism predict accidents ?
!H3ID31 ON CON_C; !does conscientiousness predict accidencts ?

!H3ID31 ON PPVT_IQC EXVSN_1C; !does IQ and  extraversion predict accidencts ?
!H3ID31 ON PPVT_IQC NEUROTC; !does IQ and  neurotocism predict accidencts ?
!H3ID31 ON PPVT_IQC CON_C; !does IQ and  conscientiousness predict accidencts ?
!bem instruments
!H3ID31 ON PPVT_IQC; !Regression IQ
!H3ID31 ON bemml_c  ; !does bemmale predict accidencts ?
!H3ID31 ON bemfml_c  ; !does bemfemale predict accidencts ?

!H3ID31 ON PPVT_IQC bemml_c  ; !does IQ and bemmale predict accidencts ?
!H3ID31 ON PPVT_IQC bemfml_c  ; !does IQ and  bemfemale predict accidencts ?
!H3ID31 ON PPVT_IQC bemml_c PVT_bmMC; !Moderation 1
!H3HS12 ON PPVT_IQC bemfml_c PVT_bmFC; !Moderation 2

!bemfml_c with H3HS7D H3HS12 H3ID28 H3ID31 PRNT_SES activity
!PPVT_IQC EXVSN_1C PVT_EXV1 NEUROTC PVT_NEUR CON_C PVT_CONS
bemml_c
!PVT_bmMC PVT_bmFC MULT OBS;
!bemml_c with H3HS7D H3HS12 H3ID28 H3ID31 PRNT_SES activity !PPVT_IQC
EXVSN_1C PVT_EXV1 NEUROTC PVT_NEUR CON_C PVT_CONS !PVT_bmMC
bemfml_c PVT_bmFC MULT OBS;
Analysis:
type = complex;
iterations = 10000;
OUTPUT: STANDARDIZED SAMPSTAT;
```

APPENDIX C

IVEware: Imputation and Variance Estimation Software

Appendix C contains the syntax used to impute the missing values for the independent variables, with the exception of the BSRI variables. IVEware software and documentation can be downloaded from http://www.isr.umich.edu/src/smp/ive/.

```
%getdata(name=ken_interact, setup=new);
  datain ken_interact.txt;
  metadata;
  delim "\t";
  variables
name=PSUSCID;
name=REGION;
name=GSWGT3_2;
name=H3HS7D;
name=H3HS12;
name=H3ID28;
name=H3ID31;
name=PARENT_SES;
name=activity;
name=PPVT_IQC;
name=EXVSN_1C;
name=PVT_EXV1;
name=NEUROTC;
name=PVT_NEUR;
name=CON_C;
name=PVT_CONS;
name=bemml_c;
name=PVT_bmMC;
name=bemfml_c;
name=PVT_bmFC;
end;
run;

/* impute the missing data, extract the first imputed dataset */
%impute(name=ken_mi1, setup=new);
  datain ken_interact;
   default continuous;
```

```
  transfer PSUSCID REGION GSWGT3_2;
  categorical H3HS7D H3HS12 H3ID28 H3ID31;
 iterations 10;
 multiples 10;
 run;

/* extract the remaining four multiply imputed datasets */
%putdata(name=ken_mi2, setup=new);
 imputation ken_mi1;
 mult 2;
 run;

%putdata(name=ken_mi3, setup=new);
 imputation ken_mi1;
 mult 3;
 run;

%putdata(name=ken_mi4, setup=new);
 imputation ken_mi1;
 mult 4;
 run;

%putdata(name=ken_mi5, setup=new);
 imputation ken_mi1;
 mult 5;
 run;

%putdata(name=ken_mi6, setup=new);
 imputation ken_mi1;
 mult 6;
 run;

%putdata(name=ken_mi7, setup=new);
 imputation ken_mi1;
 mult 7;
 run;

%putdata(name=ken_mi8, setup=new);
 imputation ken_mi1;
 mult 8;
 run;

%putdata(name=ken_mi9, setup=new);
 imputation ken_mi1;
 mult 9;
 run;
```

```
%putdata(name=ken_mi10, setup=new);
  imputation ken_mi1;
  mult 10;
  run;

%putdata; datain ken_mi1; table ken_mi1.txt; run;
%putdata; datain ken_mi2; table ken_mi2.txt; run;
%putdata; datain ken_mi3; table ken_mi3.txt; run;
%putdata; datain ken_mi4; table ken_mi4.txt; run;
%putdata; datain ken_mi5; table ken_mi5.txt; run;
%putdata; datain ken_mi6; table ken_mi6.txt; run;
%putdata; datain ken_mi7; table ken_mi7.txt; run;
%putdata; datain ken_mi8; table ken_mi8.txt; run;
%putdata; datain ken_mi9; table ken_mi9.txt; run;
%putdata; datain ken_mi10; table ken_mi10.txt; run;
```

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