PERSONALITY AND THE HEALTHY LIFESTYLE AS PREDICTORS OF PHYSICAL HEALTH:
CAN THE HEALTHY LIFESTYLE BE EXPLAINED BY PERSONALITY?

BY

GRANT WHITNEY EDMONDS

DISSERTATION

Submitted in partial fulfillment of the requirements
for the degree of Doctor of Philosophy in Psychology
in the Graduate College of the
University of Illinois at Urbana-Champaign, 2011

Urbana, Illinois

Doctoral Committee:

Professor Brent W. Roberts, Chair
Associate Professor R. Chris Fraley
Associate Professor Christopher R. Larrison
Professor Daniel K. Mroczek, Purdue University
Professor James Rounds

ABSTRACT

In health and epidemiological research, the Healthy Lifestyle (HLS) is often invoked as an explanation for inconsistent effects. Modifiable components of the HLS are advocated as a panacea for the most common threats to public health. Biases resulting from the HLS are theorized to result from covariance among its components. This covariance has not yet been formally modeled. Furthermore, no mechanism has been proposed to explain this covariance among these factors. Using three large nationally representative samples, I evaluated the HLS as a latent variable. Using structural equation modeling (SEM) I evaluated the degree to which the shared variance of HLS components is accounted for by personality traits, and tested the HLS as a mediator of the personality health relationship. Across all three samples, the HLS fits well as a latent variable, is partially accounted for by personality traits, and mediates the effects of personality traits on health. In all cases personality traits have direct effects on health independent of the HLS. These results suggest that the utility of personality traits as predictors of health exceeds that provided by commonly used lifestyle predictors.

To My Father, Roger S. Edmonds

TABLE OF CONTENTS

CHAPTER 1

INTRODUCTION

There is nothing novel in the notion that third variables can confound experimental studies, and even less novelty in the notion that these can confound the results of correlational designs. However in domains where the stakes are high, and conducting the perfect experiment is too costly, too time consuming, or simply impossible, the consumers of available research may act without regard to the notion that any study may be susceptible to the effect of an unmeasured third variable. Health and epidemiological research offer some of the most startling examples of this phenomenon, where biased effect sizes and spurious results can often be attributed the covariance of health factors referred to as the healthy lifestyle (referred to here as the HLS; for examples see: Brookhart et al., 2007; Dormuth et al., 2009; Garbe & Suissa, 2004). The HLS is the tendency of health factors, including health behaviors and social environmental factors, such as education level, to cluster together within people. In its broadest formulation the HLS includes health behaviors from multiple domains and multiple social environmental factors, as well as physiological indicators such as BMI.

Clustering of HLS factors can cause purely correlational or observational research that looks at a single behavior or environmental factor to inaccurately estimate the effect of interest as result of shared variance with unmeasured variables. As we will discuss later, results from randomized controlled or experimental studies are not necessarily immune to these effects. In some cases the presence of a confound resulting from the HLS is easily discernable. Studies showing that car ownership is related to mortality or that regularly using sunscreen will reduce the risk of suffering a heart attack eight years later are immediately viewed with suspicion (Filakti & Fox, 1995; Petitti, 2005). Unlike these obvious examples, most instances of bias resulting from the HLS are likely undetected. This results in the inflation of otherwise real effects. As researchers, we should be far more concerned with these undetected instances. My broad goals for this dissertation are to take the first steps at formalizing the HLS as a latent variable, and to investigate the hypothesis that personality variables related to physical health may account for non-random clustering of HLS factors within people. Additionally, I will evaluate the HLS as a mediator of the effects of personality traits on health.

The Healthy Lifestyle

The HLS is often invoked in health research. In its most common application the HLS is employed as an ad hoc explanation of potential bias. Given the frequency with which the healthy lifestyle is invoked by health researchers, there is surprisingly little research exploring the ways that specific features of the healthy lifestyle work together, and very little in the way of attempting to describe what the healthy lifestyle is. I will now briefly review a few studies that have attempted to formally characterize the HLS.

To date the most comprehensive formal treatment of the HLS involves attempting to evaluate its role as a source of bias in observational research on hormone replacement therapy (HRT) in women. A large body of accumulated observational research on HRT had at one time suggested that it is associated with a dramatic decrease in deaths resulting from cardiovascular disease (Grodstein & Stampfer, 1998). Later clinical trials offered puzzling results showing that HRT does not actually protect against heart disease, and in fact increases cancer risk. Given the internal validity inherent in well-conducted clinical trials, these results were viewed as more accurate representations of the true effects. In this instance, the discrepancy between observational and clinical trial research may have resulted from differences in health behaviors in the individuals who were first administered HRT. Women who voluntarily elected to receive HRT when it first became available were on average wealthier, were more likely to be a healthy weight, and generally scored better with respect to multiple risk factors for cardiovascular disease (Matthews, Kuller, Wing, Meilahn, &Plantinga, 1996). Electing to partake in new treatments is a behavior consistent with the HLS. As a result, differences in health outcomes in women who elected to take HRT versus those who did not may have been wrongly attributed to HRT when in fact they accrued through a host of HLS factors. This is a form of selection bias, and is referred to in epidemiology as a healthy user bias (HUB; Barrett-Connor & Grady, 1998).

Presumably, studies where participants are randomly assigned to a treatment are largely immune to such effects. When both clinical trial and observational data are available with respect to the same effect, there exists an opportunity to test corrections for observational research (Prentice, Langer, Anderson, & Barad, 2005). Petitti and Chen (2008) attempted to use convenient measures of the healthy lifestyle to correct effects derived from observational data. Specifically they used data from a case control study and attempted to correct effects relating hormone replacement therapy to cardiovascular disease and stroke. Results from the Women's Health Initiative randomized clinical trial of HRT served as criteria to evaluate the corrected results. Pettiti and Chen incorporated a set of healthy lifestyle indicators that included behaviors that were clearly non-causal, but also showed associations with the outcomes of interest as control variables. In addition, they controlled for a long list of traditional confounders including age and SES. The correction employed resulted in an improvement, such that results from the case controlled study were brought closer in line with the criterion study, but did not result in a complete correction. The failure of healthy lifestyle variables to offer a complete correction in this case may have resulted from the fact that the correction depended upon an incomplete set of healthy lifestyle indicators available in an ad hoc analysis. The logic employed depends on the notion that the healthy lifestyle operates as a latent variable, which can be described by the available indicators. Pettiti and Chen's analysis may have also benefited from an evaluation of the latent structure of the healthy lifestyle, and a more explicit formulation of the construct.

Often, when the HLS is invoked as a potential source of bias, it is pointed out that healthy participants may be qualitatively different from unhealthy participants in health research. An alternative approach to evaluating the HLS involves treating the HLS as a categorical variable. In an attempt to explore the nature of different health related lifestyles, Hagoel et al. (2002) ran a cluster analysis on the health behaviors of women participating in a study of interventions meant to increase the rates of mammography screening. Their cluster analysis yielded three categories based on self-reported health behaviors: health promoting, inactive, and ambivalent. These were then related to social environmental factors, and to participants' likelihood to undergo a mammogram at a future date. Women in the health-promoting cluster were more likely to self-initiate a routine mammography. Additionally, women in this cluster were more likely to undergo mammography when invited by a nurse to do so. Women in the ambivalent and inactive clusters had a higher probability of declining a mammography. Women in the health promoting lifestyle cluster were also higher on measures of SES and education. The categories generated in this sample may not reliably appear across samples and need to be replicated. Despite this, the categories and their correlates suggest that lifestyle behaviors do tend to cluster together within people, are related to social environmental factors, and have predictive validity with respect to future health behaviors.

In addition to being implicated as a confound, the HLS has also been studied as a potential boon to public health. Typically studies of this nature involve describing the additive effects of multiple health behavior domains. This type of study is based on a more narrow view of the HLS, focusing on beneficial health behaviors that are assumed to be modifiable. An example of this approach can be seen in Reeves and Rafferty (2005). Their conceptualization of the HLS involved a simple four-item index of the healthy lifestyle. This consisted of a sum of dichotomous items: non-smoking, BMI between 18.5-25.0, consuming five or more fruits and vegetables per day, and engaging in regular moderate intensity physical activity for 30 minutes or more at least five times a week. The aim of this study was to simply describe the rates of participation in modifiable health behaviors in a large sample. These were dismally low. Only 3% of the 153,805 participants reported engaging in all four health behaviors. A HLS measure like this may seem to be of limited utility, since it takes a number of continuous variables, reduces them to dichotomous variables based on somewhat arbitrary cut points, and then weights them equally. Despite this, similar measures of the healthy lifestyle have been shown to predict a variety of health outcomes including coronary heart disease (Chiuve, 2006), stroke (Chiuve et al., 2008), pancreatic cancer (Jiao et al., 2009) diabetes (Chiolero, Faeh, Paccaud, & Cornuz, 2008), and all cause mortality (Spencer, Jamrozik, Norman, & Lawrence-Brown, 2005; Tamakoshi, Tamakoshi, Lin, Yagyu, & Kikuchi, 2009).

HLS indices like those described above are constructed by selecting health behaviors that are considered established predictors of health outcomes. Typically, researchers select cut points based on their estimation of the effect size of each behavior. For example, Reeves and Rafferty chose to set the threshold for physical activity, 30 minutes or more of moderate intensity activity five or more times a week, based on a Surgeon General's report summarizing contemporary work relating physical activity to health (US Department of Health and Human Services, 1996). Yet according the hypothesis laid out here, prior work focusing on any single HLS factor is very likely to provide biased estimates.

For example, regular consumption of nuts has been linked to better cardiovascular health (Albert et al., 1998; Hu et al., 1998). Consumption of fruits and vegetables has also been linked to reduced risk of cardiovascular health (Hung et al., 2004), and to reduced cancer risk (Bosetti et al., 2005; McCann, Freudenheim, Marshall, & Graham, 2003). Obesity is an epidemic in the United States, and has been described as a leading cause of death in the United States (Allison, Fontaine, Manson, Stevens, & VanItallie, 1999; Mokdad, Marks, & Stroup, 2004). In all of the studies listed above, it was also noted that individuals who score well on the factor of interest are also better educated, more likely to eat right in general and to exercise on a regular basis. This is the norm in studies of this nature. While such caveats implicate the HLS as a potential confound, there is currently no accepted way to estimate the degree of bias emanating from the HLS, or any comprehensive way to correct for it.

Bias resulting from the tendency for health factors like these to cluster together can cause confusion that goes far beyond inflating a regression coefficient. Obesity, for example, is correlated with a host of behavioral and lifestyle factors that are not conducive to health. These include, but are not limited to, the sedentary lifestyle and poor eating habits. In studies where obesity is linked to negative health outcomes, it is often unclear if health effects accrue as a result of obesity per se, or as a result of the behavioral and lifestyle factors that typically surround obesity (Gaesser, 2003). This may occur regardless of whether obesity carries a true health risk or not. In some instances, the inflation resulting from the HLS will result in entirely artificial or spurious relationships. How then can we differentiate true effects from spurious effects in health research?

There is no single iron clad method for differentiating true and spurious effects. We must evaluate the merits of any statistical result in the context of the research design in question, and theoretical considerations. As I noted earlier some effects, such as the effect of car ownership on mortality, are so implausible that they are easily identified as spurious. In other cases, where there is a plausible causal pathway relating a specific factor to a specific outcome, there may be little reason to suspect bias. In the case of HRT, the results from observational studies that showed a protective effect of HRT on cardiovascular outcomes were supported by animal models, and short term clinical trials relating HRT to beneficial changes in high and low density cholesterol profiles. Meta-analytic results based on numerous observational studies suggested a large beneficial effect associated with HRT (Stampfer & Colditz, 1991). While it is easy to criticize researchers and doctors for giving credence to these results, it is important to note that there was a considerable amount of evidence mounted, and that in health research it is common for meta-analytic results from well-designed observational studies to coincide with those from randomized clinical trials (Concato, Shah & Horwitz, 2000). The expectation was that the meta-analytic results, all of which were consistent with research in animal models, would be borne out by randomized controlled trials. Had there been no conflict, there would have been no reason to suspect bias. At first blush we might be tempted to abandon observational research in favor of randomized clinical trials. Prior to that though we must ask, are randomized clinical trials immune to bias related to the HLS?

Randomized clinical trials, where participants are randomly assigned to treatment and control conditions, are not immune to bias resulting from the HLS. Compliance bias, also known as the adherer effect (Brookhart et al., 2007) occurs when some participants are more likely than others to reliably maintain the regimen of their assigned condition. When adherence acts as a confound, it is presumably operating as a component of the HLS and gaining predictive power from non-measured HLS factors. An early example of the adherer effect can be seen in a study evaluating the efficacy of clofibrate, a drug that presaged modern day statins (Coronary Drug Project, 1980). Clofibrate is meant to reduce the risk of coronary heart disease by modifying blood lipid levels. The Coronary Drug Project was a randomized double-blind clinical trial carried out over many years to test the efficacy of three different drugs, one being clofibrate. Five years after initiating the trial, there was no discernable difference in the control and treatment groups in terms of mortality risk with respect to clofibrate. Despite this, adherence was an important predictor of mortality in the treatment condition, such that individuals who had taken more than 80% of their prescribed drug regimen had a reduced risk of mortality over the five years studied. It would be reasonable to assume that the drug in question was only effective when it had been taken with sufficient regularity. However, the placebo group showed the same result. Individuals in the control group who had taken their placebo pills more than 80% the time had equally good health outcomes when compared to adherent participants in the treatment group. This particular study alerted health researchers to the possibility that adherence to a drug regime could be an indirect indicator of other HLS factors, and could threaten the internal validity of otherwise well designed clinical trials producing biased results.

To date the research evaluating the healthy lifestyle hypothesis has generated a number of suggestive results. However, no one has performed a comprehensive assessment of the healthy lifestyle. Currently research that attempts to control for the healthy lifestyle, or that attempts to utilize a healthy lifestyle index, is hampered by the lack of a comprehensive measure of this construct. Such research also depends upon the assumption that healthy lifestyle behaviors and social factors cohere in such a way that the healthy lifestyle can be conceived of as a single latent variable. The latent structure of the healthy lifestyle has not been explicitly evaluated. As a result these assumptions may not be merited. Both the healthy user bias and the adherence bias are theorized to emanate from the HLS. Together these biases affect both observational health research, and any clinical trial that depends on participants' continued adherence over time. Research evaluating a broad range of health behaviors and lifestyle factors that likely constitute the latent structure of the healthy lifestyle is needed.

Personality and the Healthy Lifestyle

While the healthy lifestyle has gained attention in the context of health research, there has been little work aimed at explaining the covariance of health factors that is central to the concept. Personality traits have broad predictive power across multiple domains (Roberts, Kuncel, Shiner, Caspi, & Goldberg, 2007). Healthy lifestyle factors can be divided into health behaviors and social environmental factors. Across these two domains, personality variables are related to most if not all of the factors that make up the healthy lifestyle. Therefore, one hypothesis is that personality traits are the true third variable behind the effect of the healthy lifestyle.

Social environmental factors are context dependent experiences that either detract from good health (e.g., stressful life circumstances) or promote good health (e.g., strong social connections; Adler & Matthews, 1994). For example, one distinctly stressful social environmental factor, poverty, is related to poor health outcomes for both men and women (Adler et al., 2008, 1994; Ostrove, Adler, Kuppermann, & Washington, 2000). Stressful experiences within marriage (e.g., divorce) also are linked to poor health outcomes and decreased longevity (Tucker, Friedman, Wingard, & Schwartz, 1996). In contrast, having greater levels of social connection, such as having more children and belonging to clubs, churches, and other organizations, is linked to positive health outcomes and increased longevity (Giles, Glonek, Luszcz, & Andrews, 2004; Golden, Conroy & Lawlor, 2009; House, Landis, & Umberson 1988, Litwin & Shiovitz-Ezra, 2006; Samuelsson & Dehlin, 1993; Tucker, Schwartz, Clark, & Friedman, 1999). In turn, it is clear that personality traits predict most of these social environmental factors (Ozer & Benet-Martínez, 2006; Roberts et al., 2007).

Of the big five traits related to social environmental factors, conscientiousness and neuroticism are the two traits that are most consistently related to physical health (Roberts, J. Smith, Jackson, & Edmonds, 2009). Hostility, which represents a blend of Big Five neuroticism and agreeableness, is similarly related to social environmental factors and health. My review of personality is focused on these three domains.

Conscientiousness is related to investment in many social environmental factors related to health including marriage, work environments, and social groups (Lodi-Smith & Roberts 2007). Broad measures of conscientiousness predict career success and earnings (Roberts et al., 2007; Judge, Higgins, Thoreson, &Barrick, 1999). Conscientiousness and social responsibility have been linked to greater marital stability (Roberts et al., 2007; Roberts & Bogg, 2004; Kelly & Conley, 1987; Tucker Kressin, Spiro, & Ruscio, 1998), which, in turn, predicts longevity (Tucker et al., 1996). Higher levels of social responsibility in childhood predict having more children and belonging to more organizations in adulthood, both of which contribute to increased longevity (Samuelsson & Dehlin, 1993; Tucker et al., 1999). People who were more conscientious in terms of being more controlled and industrious at the age of 18 years tended to be in higher socioeconomic work paths at 26 years of age, to feel more involved in their work, and to feel more financially secure (Roberts, Caspi, & Moffitt, 2003).

Emotional stability has strong links with interpersonal outcomes. Neuroticism is related to greater exposure to interpersonal stressors (Bolger & Zuckerman, 1995; Davila, Bradbury, Cohan, & Tochluk, 1997) and is negatively related to status in men (Anderson, John, Keltner, & Kring, 2001). Neuroticism is related to relationship dissatisfaction and conflict (Karney & Bradbury, 1997; Robins, Caspi, & Moffitt, 2000) and predicts divorce (Tucker et al., 1998). Divorce in turn is negatively related to longevity (Lund, 2004).

Hostility has established relationships with the social environment and with physical health and mortality (Smith, Glazer, Ruiz, & Gallo, 2004). It is related to cardiovascular health, such that more hostile individuals are at a greater risk for cardiovascular disease (Chang, Ford, Meoni, Wang, & Klag, 2002; Matthews, 2003). Social interaction is intrinsic to the expression of hostility, and in this context it is related to interpersonal conflict and the erosion of close relationships (Baron et al., 2006). Relationship quality is related to physiological measures of health (Birmingham, Uchino, Smith, Light, & Sanbonmatsu, 2009; Holt-Lunstad, Uchino, Smith, & Hicks, 2007). Furthermore, hostility interferes with important interpersonal interactions in such a way as to reduce the benefits that normally accrue through both giving and receiving social support (Holt-Lunstad, Smith, & Uchino, 2008). Interpersonal events of this nature are likely partially responsible for the relationship between hostility, morbidity, and mortality (Smith, 1992). The model most often invoked to explain health effects emanating from hostility within the interpersonal domain suggests that individuals high in hostility are more reactive on a physiological level in response to interpersonal stressors (Smith & Gallo, 2001).

Clearly conscientiousness, neuroticism, and hostility have established connections to social environmental factors. The most salient social environmental factor from the perspective of the healthy lifestyle is SES. While it is likely that other social environmental factors are involved in the processes linking personality to health, none are invoked with the regularity of SES with respect to the HLS. When SES is invoked as a possible confounder, this typically rests on the assumption that it covaries with other important health factors, suggesting SES is coherently related to other HLS factors. As a result, my formulation of the HLS will focus exclusively on this one social environmental factor.

Attempts to explain the relationship between SES and physical health have paralleled those aimed at describing how personality affects physical health. Both have followed very similar lines of reasoning, invoking behavioral and physiological pathways linking these predictors to physical health and mortality. These somewhat parallel lines of research have additionally demonstrated connections between SES and the personality traits conscientiousness (Hampson, Goldberg, Vogt, & Dubanoski, 2007), neuroticism (Chapman, Fiscella, Kawachi, & Duberstein, 2009; Simon, Steptoe & Wardle 2005), and hostility (Williams, 2003). The associations SES shows with personality suggest further that the covariance we would expect to see in the healthy lifestyle may be partly explained by personality. Personality has similar pervasive relationships with a second domain of the healthy lifestyle, namely health behaviors.

Personality traits such as neuroticism, conscientiousness, and hostility predict most, if not all of the health behaviors associated with the healthy lifestyle. Both low conscientiousness and high neuroticism have been associated with risky health behaviors such as smoking, drug use, risky driving behaviors, and risky sexual behaviors (Booth-Kewley & Vickers, 1994; Hoyle, Fejfar, & Miller, 2000; Lemos- Giráldez & Fidalgo-Aliste, 1997; Terracciano & Costa, 2004; Trobst, Herbst, Masters, & Costa, 2002; Walton & Roberts, 2004). Hostility is also associated with risky health behaviors including smoking, excessive alcohol consumption, and inactivity (Caspi et al., 1997; Gerrard, Gibbons, Stock, Houlian, & Dykstra, 2006; Seigler, 1994; Jessor &

Jessor, 1997). Meta-analytic results based on 194 studies demonstrate that high conscientiousness is related not only to reduced rates of risky behaviors, but also to higher rates of preventative behaviors that are likely to improve or maintain health such as regular exercise and eating a healthy diet (Bogg & Roberts, 2004).

Personality and Health

High conscientiousness and low neuroticism are established predictors of longevity (Friedman et al., 1993). Recent evidence has demonstrated that health behaviors partially mediate the relationship between personality and mortality. Risky health behaviors partially mediated the association between neuroticism and mortality in a longitudinal study of male veterans followed for 30 years (Mroczek, Spiro, & Turiano, 2009) and also in a sample of male veterans followed for 15 years (Weiss, Gale, Batty, & Deary, 2009). In a longitudinal study spanning forty years, adult health behaviors partially mediated the effects of childhood levels of conscientiousness on mortality (Hampson et al., 2007).

In addition to its role as a predictor of coronary heart disease and cardiovascular related mortality, hostility functions as a predictor of all cause mortality (Barefoot, Dahlstrom, & Williams, 1983). While much of the work relating hostility to heart disease outcomes has focused on interpersonal stressors and physiological reactivity, hostility is also related to a range of health behaviors. These include alcohol consumption, driving after drinking, inactivity, and maintenance of a healthy weight (Houston & Vavak 1991; Scherwitz et al., 1992; Siegler, 1994). These associations may help explain the broader role of hostility as a predictor of all cause mortality. Indeed, in a nine-year prospective study of over 2,000 men, the effect of hostility on all cause mortality was fully mediated by a combination of smoking and drinking behaviors, levels of physical activity, and BMI (Everson et al., 1997).

The robust relationships between personality and health raise the question of whether or not the covariance of health factors that constitutes the healthy lifestyle can be explained by personality variables. To date, research on the healthy lifestyle has ignored characteristics of the person beyond socioeconomic status. Conversely, personality research on the links between personality and health has often focused on just one trait at a time. A comprehensive evaluation of the healthy lifestyle allows us to ask to what extent the shared variance among the indicators of the healthy lifestyle can be attributed to personality traits. Furthermore, it will allow us to test the nature of the relations among personality traits, healthy lifestyle and health. Most health behavior models and health research places indicators of the healthy lifestyle between personality and health outcomes as mediators. On the other hand, if the shared variance among healthy lifestyle indicators is largely the result of personality, it may be that personality traits are the actual cause of health, not the healthy lifestyle. Placing the healthy lifestyle and personality traits in a latent variable model will allow us to test both of these possibilities.

Summary

In order to evaluate the notion that diverse factors form a coherent latent HLS variable, I investigated the following questions using structural equation modeling:

1. What is the healthy lifestyle and does it form a latent construct?

2. To what degree can the shared variance among HLS indicators be explained by personality traits?

3. Does the healthy lifestyle construct mediate the relation of personality traits to health, or alternatively, do personality traits mediate the relation of healthy lifestyle to health?

I employed cross sectional data from three large representative surveys. The first data set is a representative sample of U.S. citizens collected by Knowledge Networks in the winter of 2009 for the Health and Aging Study of Central Illinois (HASCI). The second data set is the German socio-economic panel (GSOEP), which is a representative sample of German households. In constructing the GSOEP survey, special care was taken to ensure that SES, an important component of the HLS, could be accurately assessed at the individual level. Oversampling of the wealthiest German households assured that components of SES could be adequately measured at all levels of income. The third data source, the Health and Retirement study (HRS), is a representative sample of older adults in the United States and their spouses. These data allowed me to replicate the analyses across three studies.

Analyses

Question One: Does the Healthy Lifestyle form a Coherent Latent Variable?

In order to evaluate this question I tested a formulation of the HLS using core indicators that were available across data sets. These are tobacco consumption, fruits and vegetable consumption, physical activity, BMI, and education level. These indicators were available in all data sets, with the exception of fruits and vegetable consumption, which was not available in the HRS data. I then predicted physical health outcomes using the healthy lifestyle latent variable in an SEM model.

Question Two: Do Personality Traits Account for the HLS?

I next created a series of SEM models that allowed me to evaluate the relation between personality traits and the HLS. Specifically, I created latent variables representing the Big Five in the GSOEP, and the Big Five plus hostility in the HRS and HASCI KN data sets. I modeled the latent correlations of each of these with physical health, first as single predictors, and then as simultaneous predictors. I then selected non-redundant traits and modeled these as both single and simultaneous predictors of the HLS. This allowed me to identify redundant or overlapping predictors, and also to test the amount of variance accounted for in the HLS latent variable.

Question Three: Does the HLS Mediate the Relation Between Personality Traits and Health?

Figure 1 shows a model that evaluates the degree to which the HLS latent variable mediates the effects of conscientiousness on physical health. In order to evaluate each mediation scenario, I examined model fit and the extent to which the magnitudes of the original relations (e.g., HLS to health) were mediated by the intervening variables. I tested the significance of the indirect effect by constructing confidence intervals on the indirect effect using bootstrapping methods (Preacher & Hayes, 2004). Additionally, I used standard methods for comparing the fit of non-nested SEM models, namely AIC.

CHAPTER 2

HASCI

Participants

The HASCI Knowledge Networks data were collected using an online survey administered to a representative sample of 2136 adults (51% female) from across the United States. Participants were on average 51 years old, but had an age range from 20 to 101. With respect to the racial breakdown, 79% reported Caucasian, Non-Hispanic, 9% reported Black, Non-Hispanic, 7% reported Hispanic, and 5% reported either Other or being multiracial. With respect to relationship status, 57% of participants were currently married, 19% were divorced, widowed, or currently separated, 7% were living with their partner, and 17% reported never being married. With respect to education, 32% had achieved at least a bachelor's degree, 28% reported some college education, 30% had a high school degree, and 9% had less than a high school education.

HLS Indicators

Health-related behaviors were assessed using scales and scale items drawn from the Behavioral Risk Factor Surveillance System (BRFSS; National Center for Chronic Disease Prevention and Health Promotion, 2000) and the Youth Risk Behavior Surveillance System (YRBSS; National Center for Chronic Disease Prevention and Health Promotion, 1999). Scales assessing 5 behaviors were administered to participants: tobacco consumption, physical activity, consumption of fruits and vegetables, and seatbelt use.

Tobacco consumption was assessed with four items, "During the past year, approximately how often did you smoke cigarettes?", "On the days that you smoked, how many cigarettes did you smoke?", "During the past year how often did you use chewing tobacco or snuff, such as Redman, Levi Garrett, Beechnut, Skoal, Skoal Bandits, or Copenhagen?", and "During the past year how often did you smoke cigars, little cigars, or cigarillos?"

Physical activity was assessed with three items. These items were: "During the past year, approximately how many times per week did you exercise or participate in a physical activity for at least 20 minutes that made you sweat and breathe hard?", "During the past year approximately how many times per week did you do exercises to strengthen or tone your muscles?" and "During the past year how often did you participate in physical activity for at least 30 minutes that did not make you sweat or breath hard?"

Fruits and vegetables consumption was assessed with 6 items. Participants were asked how many times in the past seven days they had eaten green salad, carrots, fruit (not counting fruit juice), potatoes (not counting french fries, fried potatoes, or potato chips), and vegetables other than green salad, carrots or potatoes.

Seatbelt use was assessed with two items. These were: "In the past year how often did you wear a seatbelt while driving a car?" and "In the past year how often did you wear a seatbelt while riding in a car driven by somebody else?"

Additional HLS indicators include BMI and SES. Height and weight were given via two self-report items. These data were used to construct a measure of BMI. Including BMI as a HLS indicator demands careful consideration. In a fully elaborated longitudinal model of health processes, BMI would operate as both a health outcome resulting from previous health behavior and biological factors, and as a predictor of future health outcomes (see Heckman, 2007). The current cross-sectional data cannot support such an elaborate model. As a result, BMI must be either treated as an indicator of physical health or as a HLS indicator, or both. Employing BMI as a HLS indicator follows the rationale of literature where BMI is include along with other modifiable health factors as part of the HLS and used to construct a predictor of health outcomes (Reeves & Rafferty, 2005). I have elected to treat BMI as an indicator of HLS, however I present several different ways of modeling BMI below.

Educational attainment was used as a measure for SES. Participants indicated their highest education level ranging from some elementary school (1) to doctoral degree (9).

Personality Predictors of Health

The AB5C (Goldberg, 1999) is designed to assess Big Five facets, which are viewed as either a blend of two higher-order traits or as a "pure" measure of a single trait. Participants completed a shortened 147-item version, which included nine conscientiousness facets, and "pure" measures of extraversion, agreeableness, neuroticism, and intellect. Each conscientiousness facet was measured using between nine and fourteen items, and participants rated whether the items reflected their actions and self-concept on a five-point scale from 1 (Very Inaccurate) to 5 (Very Accurate). The nine facet scales for conscientiousness in the AB5C are Efficiency (sample item: "Finish what I start"; scale $\alpha = .86$), Dutifulness ("Follow directions"; $\alpha = .85$), Purposefulness ("Am not easily distracted" "; $\alpha = .84$), Organization ("Have an eye for detail" "; $\alpha = .86$), Cautiousness ("Never spend more than I can afford" "; $\alpha = .73$), Rationality ("Do things in a logical order" "; $\alpha = .67$), Perfectionism ("Want everything to be done 'just right'"; $\alpha = .81$), Orderliness ("Work according to a routine" "; $\alpha = .81$), and Conscientiousness ("Am careful to avoid making mistakes" "; $\alpha = .83$). While it may be somewhat confusing to have a facet that shares its name with the broader Big Five trait under which it is subsumed, this naming convention makes sense in the larger context the AB5C. The conscientiousness facet was constructed to serve as relatively a "pure" measure of the trait, consisting of items that do not have strong secondary loadings on other Big Five factors. As a result it carries the same name as the broad factor. Aggregating across all nine facets generated a 107 item conscientiousness scale with excellent reliability ($\alpha = .96$).

The remaining AB5C factors were assessed with ten items each. Sample items for neuroticism were: change my mood a lot, keep my cool (R), and get stressed out easily (scale $\alpha = .87$). Sample items for the extroversion scale were: am the life of the party, am quite around other people (R), and start conversations ($\alpha = .83$). Sample items for intellect were: try to understand myself, am not interested in abstract ideas (R), and use difficult words ($\alpha = .80$). Sample items for agreeableness were: respect others feelings, am not interested in other peoples' problems, and like to be of service to others ($\alpha = .85$). AB5C items were rated on a one (very inaccurate) to five (very accurate) scale.

Hostility was assessed using fifteen items from the WPS aggression questionnaire (Buss & Warren 2000). Sample items include "I wonder why sometimes I feel so bitter about things" and "I wonder what people want when they are nice to me" ($\alpha = .90$) These items were rated on a one (not at all like me) to four (completely like me) scale.

Physical Health

Physical health status was assessed using the Medical Outcomes Study (MOS) 36-item short-form health survey (SF-36; Ware & Sherbourne, 1992). I employed the six subscales of the SF-36 dealing with general physical health status. These are: general health perceptions (sample item: "I am as healthy as anybody I know"), physical functioning ("Walking more than a mile"), role limitations due to physical problems ("The amount of time I've spent on work or other activities has been reduced"), energy ("I feel full of pep"), pain ("Extent to which pain interfered with normal work"), and a single item measure of social functioning ("My health problems interfered with normal social activities”). Each item was rated on a seven-point Likert scale reflecting frequency (1 = never, 7 = more than once a day) or agreement (1 = strongly disagree, 7 = strongly agree).

HASCI KN Question One: Does the HLS form a Latent Variable?

In order to evaluate the HLS as a latent variable, I first performed a confirmatory factor analyses on HLS indicators. All analyses were conducted in AMOS 18. First, a basic HLS model that could be roughly compared across data sets was evaluated. The indicators employed for the base model consisted of BMI, education level, physical activity, and tobacco consumption. This resulted in a model with fit indices that did not meet acceptable thresholds (RMSEA= .07, 90% confidence interval [CI] = .07-.12, CFI= .84). The fit of the base model was improved based on modification indices provided by AMOS. The errors for tobacco consumption and education were allowed to be correlated. This resulted in acceptable fit for the model (RMSEA= .05, 90% CI= .02-.09 CFI= .98). In the HASCI KN data, the HLS clearly formed a latent variable.

Does the HLS Predict Physical Health?

Next the HLS latent variable was used to predict physical health. In order to reduce the number of indicators used to construct a physical health latent variable, an item to construct balancing technique was used to parcel items from the SF-36 into four indicators of physical health (Little, Cunningham, Shahar, & Widaman, 2002). Items related to mental health functioning were excluded in order to construct a latent variable that would more purely represent physical health. Latent variables for physical health and the HLS were constructed and their correlation was freely estimated. The latent correlation between the HLS base model and physical health was .80 with acceptable model fit (RMSEA= .07, 90% CI= .06-.08, CFI= .95). Controlling for age and gender did not change the relationship between the HLS and physical health. Given that this represents considerable overlap between these two latent variables, I next conducted a test for discriminant validity. The covariance between the HLS and physical health latent variables was set equal to one, and the resulting model fit was compared to the previous model where this path was allowed to be freely estimated. Constraining the path equal to one resulted in significantly worse fit (χ^2_{dif} = 179.16, df_{diff}= 1, p< 0.05) suggesting that each latent variable carried some valid non-overlapping variance.

Inspection of the indicators for each variable suggested that the parceling scheme employed for physical health had resulted in four parcels that were largely representative of physical activity level. Furthermore a CFA of the HLS revealed that the physical activity indicator had the highest standardized loading on the HLS latent variable of all five of its indicators. Items related to physical activity in the SF-36 were removed and new parcels generated. The latent correlation between the HLS and this more refined physical health variable was freely estimated resulting in a correlation of .62 and acceptable overall model fit (χ^2 = 257.80, df= 18, CFI = .91, RMSEA = .08). This more focused physical health latent variable was used for the rest of the analyses. In either case, the HLS was a strong predictor of health.

Does BMI fit well as an HLS Predictor?

Since BMI can be considered to be either a predictor of health or an indicator of health, I ran a CFA of the HLS where BMI was removed. Comparing this model to my original CFA demonstrated that the new model (AIC= 78.63) did not fit as well as the full HLS model which included BMI (AIC= 68.19).

Next, I ran a series of models that tested the latent correlation of the HLS with health based on different treatments of BMI. Table 1 shows the results from four models where BMI loads on HLS, BMI is removed, BMI loads on health, BMI loads on both health and the HLS, and finally a comparison model where tobacco is removed from the HLS. The last model was included in order to evaluate the effect of removing an unequivocal HLS indicator from the model. In contrast to the tests using the CFA of the HLS, Removing BMI entirely from a model where the HLS predicted health resulted in the best fit (AIC = 256.82) followed closely by the model where tobacco consumption was removed (AIC= 264.80). Allowing BMI to load on both health and the HLS (AIC = 280.57) resulted in better model fit than allowing it to load on either health (AIC= 288.86) or the HLS (AIC= 309.78). In terms of the latent correlation, allowing BMI to load on both the HLS and health resulted in a smaller latent correlation (latent $r = .53$, $p < .05$) in comparison to allowing BMI to load on the HLS exclusively (latent $r = .62$, $p < .05$). Allowing BMI to load exclusively on health resulted in the same latent correlation produced by removing BMI entirely (latent $r = .54$, $p < .05$).

Taken together, these results are somewhat equivocal. In the CFA, removing BMI from the HLS reduced model fit. When entering the HLS as a predictor of health, removing BMI entirely resulted in the best fit. Perhaps a better evaluation of the appropriateness of BMI as an indicator is the comparison of the latent correlation between the HLS and health across different models. According to this criterion, including BMI as an indicator of the HLS results in the largest latent correlation, and therefore produces the most informative model.

HASCI KN Question 2: Do Personality Traits Account for the HLS?

While my main focus is on the personality traits conscientiousness, neuroticism and hostility, it is possible that other Big Five traits may be valuable in understanding the way that the HLS functions with respect to health. As a preliminary step, I tested the relationships between Big Five traits and hostility with physical health. For each trait, items were parceled using an item to construct balancing method (Little, Cunningham, Shahar, & Widaman, 2002). In order to better understand the degree to which personality traits may work in concert, or may be redundant with respect to health, I tested each as individual predictors, and then as simultaneous predictors of health. Relationships between single traits and physical health controlling for age and gender are reported in table 2 along with fit statistics for each model. When treated as single predictors, Big Five traits and hostility were all significant predictors of health with standardized paths ranging from .20 to .34. All of the Big Five predictors were next evaluated as simultaneous predictors of health. Fit indices and standardized path estimates for this model are reported in table 2. Model fit for this model was marginal. In the presence of other Big Five predictors, the effect of agreeableness was attenuated so that it was no longer a significant predictor of health. Agreeableness was not considered in further analyses.

Hostility was evaluated as an independent predictor of health, and also as a simultaneous predictor along with the remaining Big Five predictors. These results are presented in table 3. As a single predictor, hostility was a significant predictor of physical health (β= -.28). When entered into a model as a simultaneous predictor of health along with the remaining Big Five predictors, the effect of hostility was attenuated, but still significant (β= -.07). This combination of predictors resulted in a multiple squared correlation of .13 with health.

Having screened predictors for redundancy with respect to health, the remaining personality trait measures were evaluated as individual predictors of the HLS in separate models. Each was a significant predictor of the HLS, with standardized path estimates ranging in magnitude from .12 to .70 (see table 4 for fit statistics). Intellect stood out as an especially strong predictor, showing the strongest relationship with the HLS. On further investigation it became apparent that the very large association between intellect and the HLS resulted from a particularly large correlation between intellect and education, one of the indicators of the HLS latent variable. Removing education from the model and estimating the HLS with the remaining indicators reduced the standardized path model considerably (β= .05 p<.05). Given this problematically high correlation for what might be artifactual reasons, intellect was not considered as a predictor.

Next, I tested the degree to which extraversion, neuroticism, conscientiousness and hostility overlapped as predictors of the HLS. A model was constructed where each trait predicted the HLS as an outcome while controlling for age and gender. All predictors remained significant with the exception of hostility. Standardized path estimates of the remaining predictors ranged in size from -.08 to .23. While these associations range in size from small to medium, they represent sources of non-overlapping variance associated with the HLS. Taken together, conscientiousness, extroversion and neuroticism had a multiple squared correlation of .10 with the healthy lifestyle.

If personality and the HLS are synonymous, then a single factor model including personality and HLS indicators should fit better than a multi-factor model. I tested this hypothesis with conscientiousness, since it had the highest latent correlation with the HLS. Latent variables estimating conscientiousness and the HLS were entered into a model where they were allowed to covary freely. This model was compared to a model where their covariance was set to one. The two-factor model produced better fit indices (CFI = .99, RMSEA = .05) compared to the single factor model (CFI= .89, RMSEA = .15). A Chi squared difference test demonstrated that the two-factor model produced significantly better fit (χ^2_{dif} = 1127.50, df_{diff}= 1, p< 0.05). The HLS and personality are distinct entities. Personality traits are clearly related to the HLS, but do not account for it entirely.

HASCI KN Question 3: Does the HLS Mediate the Effects of Personality Traits on Physical Health?

The HLS was evaluated as a mediator of the effects of personality on health[1]. Separate models were designed to test for mediation of the effects of conscientiousness, neuroticism, extraversion, and hostility on health. Mediation was evaluated using nested models. For example in the case of conscientiousness, the full model (depicted in figure 1) includes three paths; conscientiousness predicting the HLS (path A), the HLS as a predictor of physical health (path B), and conscientiousness as a predictor of physical health (path C/C'). This model is compared to a nested model where path B is constrained to be zero. While an observed reduction in the C path is an indication of the presence of mediation, formal tests for mediation in an SEM framework can be made by 1) comparing the fit of a model where the mediation path is unconstrained to the fit of a nested model where the coefficient of this path is restricted to zero 2) constructing confidence intervals on the indirect effect of the predictor on the outcome in the presence of the mediator. Table 5 reports model fit indices and estimates of the indirect effect for each model. In every case the HLS acts as a partial mediator, as evidenced by significant X^2 difference tests, and significant indirect paths in each model.

The HLS as a Simultaneous Mediator of Multiple Traits

Each of the single traits that had been evaluated in the previous mediation models with the HLS were then entered into one model in order to evaluate the degree to which their indirect effects on health are independent or overlapping. Standardized path estimates and fit statistics for full and nested models for each trait, the indirect effect of each trait on health in the presence of

[1] Across all three studies models were evaluated where the direction of mediation was reversed, such that personality traits were placed as causally intermediary to the HLS and health. In every instance the indirect effects were dramatically reduced. While it is not possible to make strong claims about the direction of mediation based solely on cross sectional data, reversing the direction of mediation in these case does not appear tenable.

the mediator, bootstrapped confidence intervals on the indirect effect, and estimates of the magnitude of mediation are reported in table 6. The fit of the full model was significantly improved over the nested model (χ^2_{dif} = 226.99, df_{diff}= 1, p< 0.05). Both conscientiousness and extraversion had significant indirect paths with respect to health. The indirect paths for neuroticism and hostility were not significant. Two separate models were constructed in order to evaluate the degree to which hostility and neuroticism overlap with conscientiousness and extraversion in the absence of each other. In these models both neuroticism and hostility show significant indirect paths (see tables 7 and 8). With the exception of neuroticism and hostility, the effects of personality traits were relatively independent of each other. None of the effects of personality were fully mediated by the healthy lifestyle, indicating further that independent effects of each trait predicted health above and beyond the HLS.

Summary of HASCI KN Findings

Modeling the HLS as a latent variable resulted in a model that fit well, thus indicating that the indicators of the HLS form a latent variable. Physical heath was strongly related to the HLS. The HLS was not synonymous with personality. Personality traits were related to the HLS. Conscientiousness, extroversion, neuroticism and hostility all had effects on health that are partially mediated by HLS. The effects of personality traits on health operated partially through the HLS, but a portion of these effects operate independent of this mediator.

CHAPTER 3
GSOEP

Participants

The German Socio-Economic Panel Study (GSOEP) is an ongoing longitudinal study of German households. Data collection began in 1984. The sample is based on a multi-stage random sampling technique. In the households sampled, all members over the age of 16 were asked to participate. This sampling method results in a nationally representative sample of German households, with participants' ages ranging from 16 to the mid 80's. In order to use the GSOEP for the current project, data must be collapsed across waves. For example, while health is measured in every wave of the GSOEP, personality was assessed only once, in the 15^{th} wave, and health behaviors were assessed in the 14^{th} wave. I collapsed data across the 14^{th}, 15^{th}, and 16^{th} waves of the GSOEP data. The data for participants in these waves were collected over the years 2004 to 2006. The total sample size is approximately 20,850.

Prior to conducting analyses using the GSOEP data, a random sample of the data was selected such that one person was randomly selected from each household in the survey. The resulting random sample was 44.3% men and 55.7% women (total n= 7732). Ages of the participants in the sampled data set ranged from nineteen to ninety-seven years with a mean age of 53. The gender distribution of the random sample differed slightly from the overall GSOEP sample, which consisted of 47.5% men and 52.5% women. Multiple random samples generated the same gender ratio. This difference resulted from the random selection method used, which selected single member households by default. Single member households were more likely to be occupied by women than men (38.6% men versus 61.4% women). Removing half of the single member households from the data set corrected the discrepancy in gender ratios. Analyses conducted with either the original random sample, or one with the gender ratio corrected resulted in identical fit indices and path estimates. The results presented here employ the original random sample.

Materials

HLS Indicators

The GSOEP offers an array of measures that can be used to model the healthy lifestyle as a latent variable. These include social environmental factors, and health behaviors. The social environmental factors assessed include common indicators of SES. One of the strengths of the GSOEP in this regard rests in its detailed assessment of SES. Typically SES is estimated using a single measure of education, career attainment, or wealth. All of these are included in the GSOEP data. Variables pertaining to personal wealth are measured with greater accuracy than in many previous economic panel studies.

The health behaviors measured in the GSOEP include drinking, smoking, diet, and physical activity. Smoking behaviors are assessed with two items: “Do you currently smoke cigarettes, a pipe, or cigars?” and “How many cigarettes, pipes or cigars do you smoke per day?” Diet is evaluated with a single item, “Do you eat a health conscious diet?” Physical activity is measured with the item “How often do you engage in recreational sports?”

Physical Health Indicators

The GSOEP includes a short version of the Sf-36, the SF-12. This measure covers similar domains as the SF-36, but using just one or two items for each content area. This allowed me to construct a very similar health outcome measure to the one employed in the HASCI KN models.

I removed items from the SF-12 that measured mental health functioning, and items that directly addressed physical activity levels. This left three single items indicators covering self-rated global health status, physical pain, and vitality or energy level. General health was assessed by asking "In general, would you say your health is excellent, very good, good, fair, or poor?" Pain was assessed with the item "During the past four weeks, how much did pain interfere with your normal work including both work outside the home and housework? Vitality was assessed with the item "Did you have a lot of energy?" which was rated on a one (all of the time) to six (none of the time) scale.

Psychological Predictors

Big five personality dimensions were measured using a fifteen-item version of the BFI (John & Shrivastava, 1999). Three items were used to measure each of the big five. Participants rated each item on a seven-point scale (1 = "Does not apply" to 7 = "Does Apply"). Conscientiousness was assessed with these three items: thorough worker, tend to be lazy (R) and carry out tasks efficiently ($\alpha = .60$). Neuroticism was measured using three items: worry a lot, deal well with stress (R) and somewhat nervous ($\alpha = .62$). Extroversion was assessed using the items: am sociable, reserved, and am communicative ($\alpha = .65$). Agreeableness was assessed with: friendly with others, am sometimes too coarse with others (R), and able to forgive ($\alpha = .52$). Openness was assessed using: am original, value artistic experiences, have a lively imagination ($\alpha = .63$).

GSOEP Question One: Does the HLS form a Latent Variable?

In order to evaluate the HLS as a latent variable, I performed a confirmatory factor analysis on HLS indicators in the GSOEP data. A basic HLS variable that was roughly comparable to the variable created in the HASCI KN data set was evaluated. The indicators consisted of BMI, years of education, frequency of physical activity, and daily tobacco consumption. This produced a model with acceptable fit (RMSEA= .06, 90% CI= .05-.07 CFI= .91). Clearly the HLS formed a latent variable.

Does the HLS Predict Physical Health?

Next the HLS latent variable was used to predict physical health. Three single item indicators from the SF-12 were used to model physical heath in a way that approximated the HASCI KN health outcome as closely as possible. The resulting latent variable was placed in a model with the HLS and their correlation was freely estimated. The latent correlation between the HLS base model and physical health was .34 with acceptable model fit (RMSEA= .07, 90% CI= .06-.07, CFI= .92). Controlling for age and gender did not appreciably change the relationship between the HLS and physical health.

I next conducted a test for discriminant validity. The covariance between the HLS and physical health latent variables was set equal to one and the resulting model fit was compared to the previous model where this path was allowed to be freely estimated. Constraining the path equal to one resulted in significantly worse fit (χ^2_{dif} = 62.30, df_{diff}= 1, p< 0.05) suggesting that each latent variable was distinct. These results support the conclusion that the HLS is a moderately good predictor of health in the GSOEP.

Does BMI fit well as an HLS Predictor?

In order to evaluate BMI as an indicator of the HLS**,** I first ran a CFA of the HLS where BMI was removed. Comparing this model to my original CFA demonstrated that the new model (AIC= 63.36) fit better than the full HLS model which included BMI (AIC= 132.50).

Next, I ran models that tested the latent correlation of the HLS with health using the same rationale applied in the HASCI KN data. Table 9 shows the results from four models where BMI loads on HLS, is removed, loads on health, loads on both health and the HLS, and finally a comparison model where tobacco is removed from the HLS. The last model was included in order to evaluate the effect of removing an unequivocal HLS indicator from the model. Allowing BMI to load on both the HLS and health resulted in the best fit (AIC = 392.30). When BMI was used as an indicator of health exclusively the model fit (AIC = 502.32) was better than that achieved when BMI was removed from the model entirely (AIC = 541.60) and also better than when it was employed as an indicator for the HLS (AIC= 732.68). Including BMI as an indicator of the HLS resulted in the highest latent correlation between the HLS and health (latent r = .34). Removing BMI entirely resulted in the next largest latent correlation (latent r = .32) followed by the model where BMI loaded on both the HLS and health (latent r = .29). Allowing BMI to load exclusively on health produced the lowest latent correlation (latent r = .25). In the GSOEP data, BMI functions best as an indicator of both the HLS and health in terms of AIC. However, the best prediction of heath was achieved by using BMI as an indicator of HLS, which is consistent with the results from the HASCI KN data. Despite not providing the best fit, there is no evidence that testing the theoretically relevant idea that that BMI is an indicator of the HLS is necessarily flawed or detrimental to the models being tested. For the rest of my analyses I used BMI as an indicator of the HLS.

GSOEP Question Two: Do Personality Traits Account for the HLS?

As a preliminary step, I tested the relationships between Big Five traits and physical health. Since the personality inventory employed by the GSOEP employed three items for each Big Five domain, latent variables for these were constructed using single item indicators. In order to better understand the degree to which personality traits may work in concert, or may be redundant with respect to health, I tested each as individual predictors, and then as simultaneous predictors of health. Relationships between single traits and physical health controlling for age and gender are reported in table 10 along with fit statistics for each model.

Replicating the results in the HASCI KN data, the Big Five were all significant predictors of health when examined singly. These effects operated independently of the effects of age and gender. The associations between personality traits ranged from small (β= .09, p< .05 for agreeableness) to moderate (β= -.34, p< .05 for neuroticism). When all five predictors were entered simultaneously, the model fit suffered (RMSEA= .09, 90% CI= .09-.09, CFI= .71). Consistent with the results seen in the HASCI KN data, agreeableness was completely attenuated and was no longer a significant predictor of health. Neuroticism on the other hand experienced little if any attenuation (β= -34, p< .05 versus β= -32, p< .05). Agreeableness was not considered in further analyses.

Having screened predictors for redundancy with respect to health, the remaining predictors were next evaluated as individual predictors of the HLS in separate models. Each personality trait was a significant predictor of the HLS while controlling for age and gender, however none of these models resulted in acceptable model fit (see table 11). Removing the control variables from the model did not appreciably alter the path estimates of interest, but did improve model fit (table 12). The standardized path estimates ranged in magnitude from .08 to .35 (see table 12 for fit statistics). Openness stood out as the strongest predictor of the HLS. In order to evaluate the degree to which the association with openness resulted from its association with education, I constructed a model where education was removed from the HLS. Estimating the relationship with the remaining HLS indicators reduced the standardized path only slightly (β= .35 p<.05 versus β= .32 p<.05; RMSEA = .07, 90% CI = .06-.07, CFI = .91). Unlike the models constructed using the HASCI KN data, openness did not appear to function in a problematic way within the model. This may have resulted from the aspect of openness tapped by the mini-BFI scale. The three items, “I have a lively imagination”, “I value artistic experiences”, and “I am original” have more to do with the imaginative aspect of openness as opposed to measures that tap the intellect component of openness.

Next, I tested the degree to which extraversion, neuroticism, conscientiousness and openness overlapped as predictors of the HLS. A model was constructed where each trait predicted the HLS as an outcome while age and gender were controlled for. The resultant model fit did not meet acceptable thresholds, and was not improved by removing the control variables from the model (tables 13 and 14). Openness was not attenuated as a predictor, while all other predictors’ effects were attenuated to varying degrees. Extraversion was no longer a significant predictor of the HLS. The squared multiple correlation resulting from this combination of predictors was .17.

Openness showed the largest relationship with the HLS of any personality trait evaluated in the GSOEP. I next evaluated a single factor model using HLS indicators and indicators of openness versus a two factor model. The two-factor model fit better as evidenced by a chi squared difference test ($\chi^2_{dif} = 259.00$, $df_{diff} = 1$, $p < 0.05$).

All of the observed associations between personality and the HLS in the GSOEP were considerably smaller than those observed in the HASCI KN data. Given that personality was measured using three-item scales that did not measure the full breadth of each trait, the GSOEP does not offer authoritative answers regarding the degree to which the HLS is associated with personality. Despite these caveats, all five of the big five showed some relationship with the HLS. This likely resulted from two things 1) even narrow trait measures will show small effects with respect to health and factors related to health and 2) the very large samples available in the

GSOEP data allow for the detection of small effects. Overall, this demonstrates that personality traits account for a considerable portion of the HLS, but not enough to lead one to conclude that they are the same construct.

GSOEP Question Three: Does the HLS Mediate the Effects of Personality Traits on Physical Health?

The HLS was evaluated as a mediator of the effects of personality traits on health. Separate models were designed to test for mediation of the effects of conscientiousness, neuroticism, extraversion, and openness on health. Mediation was evaluated using the same methods employed in the HASCI KN data. Table 13 reports model fit indices and estimates of the indirect effects for each model. Controlling for age and gender did not appreciably alter the path estimates of these models, but did reduce model fit. The results presented in table 13 do not control for age and gender. In every case the HLS acted as a partial mediator, as evidenced by significant χ^2 difference tests, and significant indirect paths in each model. In every case except intellect, the indirect effects were small (*β's* range from .04 to .06). The indirect effect for intellect was larger (β= .11). Once again, these models are likely hampered by limits of the available personality variables. Despite these limitations the HLS mediates the effects of multiple traits on health.

Conscientiousness, neuroticism and openness were then entered into one model in order to evaluate the degree to which their indirect effects on health via the HLS were independent or overlapping. Extroversion was excluded since it was not a significant predictor of the HLS in the presence of other personality predictors. Standardized path estimates and fit statistics for full and nested models for each trait, the indirect effect of each trait on health in the presence of the mediator, bootstrapped confidence intervals on the indirect effect, and estimates of the magnitude of mediation are reported in table 14. The fit of the full model was significantly improved over the nested model (χ^2_{dif} = 240.67, df_{diff}= 1, p< 0.05). However, the fit in either model was marginal at best. Indirect paths for each predictor were significant. It should be noted that the indirect paths for neuroticism and conscientiousness were very small, and it is likely that they only achieved significance as a result of the large sample size employed.

Summary of GSOEP Findings

In the GSOEP data, the HLS formed a coherent latent variable. The HLS has moderate predictive validity with respect to health, and is a distinct entity from health. Including BMI in the HLS was not problematic and resulted in the largest latent correlation between health and the HLS. However allowing BMI to load on both health and the HLS produced better model fit. Conscientiousness, intellect, extroversion, and neuroticism were relatively independent predictors of both the HLS and health. Of these traits intellect had the largest association with the HLS. The HLS partially mediated the effects of these traits on health, such that personality traits demonstrated predictive validity on health above and beyond the HLS.

CHAPTER 4

HRS

Participants

The HRS is an ongoing national longitudinal study of Americans over the age of 50. The data that used for this study come from the 2006 wave of data collection. The overall HRS sample consists of a nationally representative sample of households where the initial participants are over the age of 50, and the spouse or partner of each participant is interviewed regardless of age. The full HRS sample consists of approximately 22,000 participants. In 2006 a random sample of half of the overall HRS sample was contacted for an enhanced face-to-face interview. A leave behind pen-and-paper questionnaire was distributed to participants who consented to the face-to-face interview. Many of the variables I used in the current analyses were collected in the leave behind survey. Approximately 7,540 participants completed and mailed in the leave behind questionnaire. Most, but not the entire HRS sample consists of couples where individuals within couples may be correlated on important variables of interest. In order to remove the possibility that correlations with dyads might lead to non-random dependency in the data, a random sample of participants was selected for this analysis. One person was randomly sampled from each household in the survey. The resulting sample was 63% women and 37% men (total n= 5193). Ages of the participants in the sampled data set ranged from thirty to one-hundred four years with a mean age of sixty-eight. Multiple random samples resulted in the same gender ratio. The gender ratio of the sample data set differed from the source data file. The original data file was comprised of 59% women and 41% men. This discrepancy resulted from the same source as the discrepancy in the GSOEP data, namely a higher rate of women in single member households.

Removing half of the single member households from the randomly selected data set reproduced the gender ratio of the original data set. Analyses conducted on this data set resulted in identical fit indices and path estimates as those conducted in the original random sample. The analyses presented here employ the original random sample.

HLS Indicators

The HRS provides an impressive set of items that can be used to construct a latent variable representing the HLS. Broadly these can be classified as health behaviors, and social environmental factors.

The heath behaviors category includes detailed information on tobacco consumption and physical activity level. Tobacco consumption was evaluated by first asking if participants had ever smoked, meaning that they had consumed more than 100 cigarettes in their lifetime, and if they were current smokers. Current smokers were asked to indicate the number of cigarettes or packs they typically smoked per day.

Physical activity was assessed with three items. These covered different types of physical activity, ranging from vigorous (i.e. aerobics) to mild (i.e. vacuuming). These were rated on a four-point scale, from more than once a week, to hardly ever or never. An example item would be, "How often do you take part in sports or activities that are vigorous, such as running or jogging, swimming, cycling, aerobics or gym workout, tennis, or digging with a spade or shovel?"

Measurement of SES

Year of education was used a proxy for SES.

Personality Predictors of Health

Big five personality dimensions were measured with a twenty-six item adjective scale. This short measure was originally constructed by Lachman and Weaver (1997) for the MIDUS study. Eight additional items were added from the Mini-IPIP scales for neuroticism and conscientiousness (Donellan, Oswald, Bard, & Lucas, 2006). Conscientiousness items from the Lachman and Weaver measure consisted of self-ratings on five adjectives: responsible, organized, careless, hardworking, and thorough. These were rated on a four-point scale from 1 (a lot) to 4 (not at all). Items from the mini-IPIP consist of short phrases. The items selected for conscientiousness were: get chore done right away, often forget to put things back in their proper place (reverse scored), like order, and make a mess of things (R). These were rated on a five-point scale ranging from 1 (very accurate) to 5 (very inaccurate). Items from both measures were standardized so they could be combined into a single nine item conscientiousness scale (α = .76). Neuroticism items from the Lachman and Weaver measure consisted of self-ratings on four adjectives: moody, worrying, nervous, and calm (R). Neuroticism items selected from the mini-IPIP were: am relaxed most of the time (R), have frequent mood swings, get upset easily, and seldom feel blue (R). Items from both measures were standardized so they could be combined into a single neuroticism scale (α = .72). Extroversion was measured using the items outgoing, friendly, lively, active, and talkative (α = .75). Agreeableness was measured using helpful, warm, caring, softhearted, and sympathetic (α = .78). Openness was measured using the items creative, imaginative, intelligent, curious, broad-minded, sophisticated, and adventurous (α = .79).

Hostility was evaluated using five items from the Cook-Medley hostility inventory (Cook & Medley, 1954; Costa, Zonderman, McCrae & Williams, 1986). These were: Most people inwardly dislike putting themselves out to help other people, most people will use somewhat unfair means to gain profit or an advantage rather than lose it, no one cares much what happens to you, I think most people would lie in order to get ahead, and I commonly wonder what hidden reasons another person may have for doing something nice for me ($\alpha = .79$). These were rated on a 1 (strongly agree) to 6 (strongly disagree) scale.

Physical Health

The HRS does not contain variables that allow for an exact replication of the physical health outcomes employed in the HASCI KN and GSOEP data. In order to approximate the health measure used in the other two studies, items covering self-reported health, self-reported pain, and ADL's were used as indicators of the HLS.

Global self-rated health was assessed with two items: "Would you say your health is excellent, very good, good, fair, or poor?" and "Compared with your health when we last talked with you, would you say that your health is better now, about the same, or worse?" These items were scored on a five point Likert scale.

In order to evaluate ADLs, participants were asked if their health prevented them from doing any of thirteen specific physical tasks. Examples of these include getting up from a chair after sitting for long periods, and climbing several flights of stairs without resting. ADL items were screened in order to remove those that dealt directly with physical activity levels, so that the outcome variable could not be construed as redundant with HLS indicators. This resulted in five ADL items. Each ADL item was scored as a dichotomous variable.

Pain was assessed with a single item: "Are you often troubled with pain?" This was scored on a three point scale. Since it was not feasible to average cross Likert type and dichotomous variables, these were parceled according to their content. The self-rated health items were averaged together, the ADL's were summed, and the pain item was used as a single item indicator.

HRS Question One: Does the HLS form a Latent Variable?

In order to evaluate the HLS as a latent variable, I performed a confirmatory factor analysis on HLS indicators using the HRS data. A basic HLS variable that could be roughly compared across data sets was evaluated. The indicators employed for the base model closely matched those used in the KN data set and consisted of BMI, years of education, frequency of physical activity, and daily tobacco consumption. This produced a model with good fit (RMSEA= .05, 90% CI= .04-.06 CFI= .95).

Does the HLS Predict Physical Health?

Next the HLS latent variable was used to predict physical health. A model including the base HLS latent variable and a physical health latent variable was constructed and their correlation was freely estimated. The latent correlation between the HLS base model and physical health was .87 with good model fit (RMSEA= .06, 90% CI= .06-.07, CFI= .89). Controlling for age and gender reduced the magnitude of the effect (β= .78, RMSEA= .033, 90% CI= .00-.06, CFI= .97). Since the correlation between the HLS and health is quite large in this sample, I tested a single factor model that included indicators for both constructs. This is effectively a test for discriminate validity. The correlation between these two variables was constrained to be one in order to see if that improved fit. Constraining the path equal to one resulted in significantly worse fit (χ^2_{dif} = 5308.1, df_{diff}= 1, p< 0.05) suggesting that each latent variable carried some valid non-overlapping variance; health and the HLS are distinct.

Does BMI fit well as an HLS predictor?

Following the same logic of the previous two studies, I evaluated BMI as an indicator of the HLS. In the HRS data set, the HLS was estimated with four indicators. In this case, removing one indicator from the HLS resulted in a perfectly identified model. Testing CFAs of the HLS with and without BMI included is therefore not informative. It is however possible to conduct tests analogous to those run on the HASCI KN and GSOEP data sets based on the latent correlation between the HLS and health.

The same five models testing the latent correlation between the HLS and health given different treatments of BMI that were tested for the HASCI KN and GSOEP data were tested for the HRS. These include models where BMI loads on the HLS, is removed from the model, loads on health exclusively, loads on both health and the HLS, and finally a comparison model where tobacco consumption is removed from the HLS. Latent correlations between the HLS and health, along with fit indices for each model are presented in table 15. The best model fit was achieved by removing BMI entirely. Removing tobacco consumption resulted in the next best fitting model (AIC= 183.81). Allowing BMI to load on both health and the HLS resulted in better fit (AIC = 240.74) than either allowing BMI to load on health exclusively (AIC = 243.07) or allowing BMI to load on exclusively on the HLS (AIC = 263.30). Once again, using BMI as an HLS indicator does not provide the best fit. It does however result in a larger latent correlation between the HLS and physical health (latent r = .92) than removing BMI (latent r = .82) or allowing it to load on both health and the HLS (latent r = .82). Moreover, using BMI as an indicator of the HLS does not prevent the HLS from fitting well as a model, and allows for the evaluation of a consistent set of HLS indicators across models that do, and do not, include health. Based on this reasoning I used BMI as an indicator of the HLS exclusively.

HRS Question Two: Do Personality Traits Account for the HLS?

As a preliminary step, I tested the relationships between Big Five traits with respect to physical health. The number of items used to measure each Big Five domain range from five to seven. In order to employ a consistent strategy across constructs I ran EFA's for all of the big five traits and selected the four highest loading items for each trait. I then used the same procedure to select items for hostility. The selected items were used as single item indicators for each Big Five factor and hostility. In order to better understand the degree to which personality traits may work in concert or may be redundant with respect to health, I tested each as individual predictors and then as simultaneous predictors of health.

Relationships between single traits and physical health controlling for age and gender are reported in table 16 along with fit statistics for each model. Replicating the results in the HASCI KN data, the Big Five were all significant predictors of health when examined singly. These effects operated above and beyond the effects of age and gender. The associations between personality traits range from small (β= .12, p< .05 for agreeableness) to moderately large (β= .39, p< .05 for conscientiousness). Each single predictor model produced good fit with CFIs ranging from .90 to .97, and RMSEAs ranging from .04 to .07. When all five predictors were entered simultaneously, the model fit suffered (RMSEA= .08, 90% CI= .08-.08, CFI= .70). Using all five predictors simultaneously resulted in a squared multiple correlation of .25 on health. In contrast with the results seen in the HASCI KN data, the effect of agreeableness was not completely attenuated in the presence of other predictors. Openness on the other hand was not a significant predictor when entered with the other Big Five and hostility. Openness was not considered in further analyses of the HRS data.

Having screened predictors for redundancy with respect to health, the remaining predictors were next evaluated as individual predictors of the HLS in separate models while controlling for age and gender. With the exception of agreeableness, each was a significant predictor of the HLS with standardized path estimates ranging from .14 (extroversion) to -.45 (hostility). Neuroticism presented a problem in that this model produced a negative variance for the HLS error term. Setting the error term to zero resulted in a model that successfully converged. Results for neuroticism in table 17 are derived from a model with this added constraint.

Next, I tested the degree to which conscientiousness, neuroticism, extraversion, and hostility overlapped as predictors of the HLS. A model was constructed where each trait predicted the HLS as an outcome while age and gender were controlled for. The resultant model produced fit statistics that were marginal (RMSEA= .06, 90% CI= .06-.07, CFI= .78). Extroversion was not a significant predictor of the HLS in the presence of other predictors. All other predictors remained significant but were slightly attenuated, with *βs* ranging in magnitude from .20 to .40. This combination of predictors produced a squared multiple correlation of .44 on the HLS. Table 17 presents these side by side with the estimates based on single predictor models. In contrast to the HASCI KN data, neuroticism and hostility remained largely independent of each other with respect to the HLS.

Since hostility had the largest latent correlation with the HLS, a single factor model was tested using indicators of these two constructs. The two-factor model produced significantly better fit (X^2_{dif} = 161.30, df_{diff}= 1, p< 0.05). These results suggest that hostility and the HLS are better modeled as distinct constructs.

The overall picture that emerges is one where conscientiousness, neuroticism and hostility have sizeable non-overlapping effects with respect to both the HLS and physical health.

These three personality traits account for considerable proportions of the variance of the HLS. However, personality traits remain distinct from the HLS.

HRS Question Three: Does the HLS Mediate the Effects of Personality Traits on Physical Health?

The HLS was evaluated as a mediator of the effects of personality on health. Separate models were designed to test for mediation of the effects of conscientiousness, neuroticism, extraversion, and hostility on health. Mediation was evaluated using the same methods employed in the HASCI KN data. Table 18 reports model fit indices and estimates of the indirect effects for each model. Conscientiousness had an effect on physical health that was completely attenuated in the presence of the mediator, consistent with full mediation (β=.05, p<.05). In every other case the HLS acted as a partial mediator as evidenced by significant χ^2 difference tests, and significant indirect paths in each model. Conscientiousness and hostility had the largest indirect paths (βs= .44 and -.51 respectively). This makes sense given that in SEM the magnitude of the indirect effect is a direct approximation of the degree to which an effect is mediated.

The HLS as a Simultaneous Mediator of Multiple Traits

Conscientiousness, neuroticism and hostility were then entered into one model in order to evaluate the degree to which their indirect effects on health via the HLS are independent or overlapping. Standardized path estimates and fit statistics for full and nested models for each trait, the indirect effect of each trait on health in the presence of the mediator, bootstrapped confidence intervals on the indirect effect, and estimates of the magnitude of mediation are reported in table 19. The fit of the full model was significantly improved over the nested model (χ^2_{dif} = 417.94, df_{diff}= 1, p< 0.05). Conscientiousness, neuroticism, and hostility all showed indirect effects comparable to those reported in their single predictor mediation models. Once again the effect of conscientiousness on health was fully mediated. The effect of neuroticism on health was partially attenuated. The multiple squared correlation with health was .82, which is extremely large. One problem arose in this model. The effect of the HLS on health was magnified such that the standardized path equaled one (β= 1.00). Clearly, the effects of conscientiousness, neuroticism, and hostility are all mediated by the HLS. However, the degree to which the effect of the HLS on health was inflated in this model indicates that these results should be interpreted with some caution.

Summary of HRS Findings

In the HRS data, the HLS formed a latent variable. The HLS had a very high level of predictive validity with respect to health. Despite a very high correlation between the two, the HLS and health are distinct latent variables. Including BMI in the HLS was not problematic, and when compared to other treatments of BMI, resulted in the largest correlation between health and the HLS. Allowing BMI to load on both the HLS and health enhanced model fit in comparison to allowing BMI to load on just one of these. Conscientiousness, neuroticism, and hostility were relatively independent predictors of both health and the HLS. Of these conscientiousness had the largest relationship with health. Hostility and conscientiousness both had large relationships with the HLS that were similar in magnitude. The HLS completely mediated the effect of conscientiousness on health, and partially mediated the effect of neuroticism on health. The effect of hostility on health reversed sign in the presence of the HLS as a mediator. This may have been accounted for by inflated magnitude of the effect to the HLS on health, which indicates that this model should be interpreted with caution.

CHAPTER 5

DISCUSSION

In the three studies I conducted I sought to answer three questions: 1) Does the HLS form a latent variable? 2) Does personality account for the HLS? And 3) does the HLS mediate the relationship between personality and health? The answer to the first question is unequivocal; the HLS formed a good fitting latent variable across all three data sets. Across the three studies, Conscientiousness and neuroticism were the most consistent predictors of the HLS. Combining personality traits accounted for nearly half of the variance in the HLS. Personality traits do not account entirely for the HLS, however the magnitude of the relation between traits and HLS was large. Finally, the HLS fully or partially mediated the effects the personality traits I evaluated as predictors of health.

Personality Traits and the HLS

Prior to evaluating personality traits as predictors of the HLS, I tested them as predictors of physical health. When modeled as single predictors of health, all of the Big Five factors and hostility were significant predictors across all three samples. This resulted, in part, from the very large sample sizes employed here. The power afforded in these samples allowed for very small effects to be detected. When entered as simultaneous predictors, agreeableness was no longer a significant predictor of health in the GSOEP and HASCI KN data sets.

Next, I used personality traits to predict HLS. Extroversion was a redundant predictor of the HLS in both the HRS and GSOEP data. This contrasts with the HASCI KN data where extroversion was related to both physical health and the HLS. Extroversion has been implicated in some health processes, however extroversion is not a consistently beneficial predictor of health related factors across studies. For example, higher levels of extroversion were associated with longevity after infection with HIV (Ironson, O'Cleirigh, Schneiderman, Weiss, & Costa, 2008) and an increased likelihood of appropriately using emergency room resources in old age (Chapman et al., 2009). Higher levels of extroversion also predict activity level, an important aspect of the HLS. At the same time, extroversion is associated with smoking risk, and with alcohol consumption (Hampson et al., 2006; Hampson et al., 2007). Overall, extroversion has associations with health behaviors and health that are not necessarily positive. The inconsistent results across the three samples evaluated here may result from a combination of heterogeneous health positive and health negative effects associated with extroversion. Alternatively the different results for extroversion across these studies may have resulted from differences in the extroversion scales used in each study.

Intellect was a problematic predictor in the HASCI KN data. It had a very large correlation with the HLS that resulted from a large association with education. Models in the HASCI KN data containing education as a HLS indicator and intellect as a predictor were of questionable value. Removing education from the HLS in this model reduced the relationship between intellect and the HLS to a more reasonable magnitude. In the HRS, the effect of intellect on health was completely attenuated when modeled simultaneously with other traits, and was not evaluated in mediation models with the HLS. In contrast to the result reported for the HASCI KN data, openness was not a problematic predictor in the GSOEP data.

The different results for intellect/openness across these data sets likely resulted from differences in content across the intellect measures used. Intellect/openness measures typically contain some mixture of three broad aspects; imagination, introspection, and intellectual knowledge (Saucier 1994). The measure employed in the HASCI KN data consists almost entirely of items covering the intellectual knowledge domain, while the measure employed in the GSOEP consists entirely of items that fit with the imaginative aspects of the domain. Intellect/openness scales laden with items tapping intellectual knowledge show persistent moderate correlations with general intelligence, whereas scales that cover the imaginative domain do not. It is possible that the association between intellect and education that we see in the HASCI KN data resulted from this association. In the GSOPE data, it is especially interesting that a short measure consisting entirely of items taping the imaginative facet of intellect was related to both health and the HLS. This result fits with emerging evidence that this aspect of intellect/openness is related to mortality (Turiano & Mroczek, in press).

In the HRS and HASCI KN data, hostility was also related to the HLS and health when modeled as a single predictor. Models that included multiple personality traits demonstrated a tendency for hostility to overlap with neuroticism. In the HASCI KN data, these two traits operated in such similar ways, and overlapped to such a degree, that they were nearly indistinguishable. In the HRS data, a different measure of hostility was moderately related to neuroticism. In that case, hostility and neuroticism remained distinct as predictors. The difference here may have resulted in difference in the content of hostility scales used, or differences across the neuroticism scales employed. These results are not definitive, but suggest that a well-constructed neuroticism scale can subsume much of what is covered in some hostility scales. It is worth noting that agreeableness fell out as a redundant predictor of health in all three samples. This, combined with the utility of hostility as a predictor and its apparent overlap with neuroticism, suggests that in these data the effect of hostility has less to do with agreeableness than it does with neuroticism. This may result in part from the level of analysis employed here. The aspect of hostility having to do with agreeableness may become more important when looking at certain specific health outcomes as opposed to global health, or when evaluating outcomes in an interpersonal context.

The two traits that stand out as the most consistent predictors of health and the HLS across all three studies were conscientiousness and neuroticism. Their effects tended to be large, and relatively independent. The relatively small correlations demonstrated by these traits in the GSOEP data may have resulted from the narrow specificity of the trait measures employed in this particular study.

Overall, these results demonstrated that personality traits do not entirely account for the HLS. They do however account for a large portion of the HLS. Across all three samples, personality accounts for anywhere from 10% to half of the variance in the HLS. In the HRS sample, conscientiousness alone accounts for 20% of the variance in the HLS. Relationships of this magnitude implicate personality traits as important components of the health processes associated with the HLS. They also demonstrate that personality traits can be productively included in epidemiological and health research.

Mediation Models

For those traits that were related to both the HLS and health, the effects of personality on health were partially mediated by the healthy lifestyle. In the HRS, the effect of conscientiousness on health was fully mediated in the presence of other personality variables. This suggests that in the HRS, the effects of conscientiousness on health did not overlap with other traits and operated entirely through the healthy lifestyle. In studies that have evaluated mediators of the effects of personality on health, partial mediation is the norm (e.g., Lodi-Smith et al., 2010), although studies to date have not modeled the full complement of HLS indicators.

Prior studies have typically focused on one or two specific mediators. No single health behavior or health-related factor carries the full effect of personality on health. Instances of partial mediation make sense under the assumption that, in reality, other non-measured factors are mediating part of the effect. The full mediation that we see here demonstrates that in some cases the entire effect of personality on health can be mediated by the shared variance of HLS factors.

Implications for Epidemiology and Health Research

At the outset, I described a number of scenarios in health research where bias may have resulted from the covariance of health factors that we see in the HLS. Under the assumption that the health outcome here is analogous to the health outcomes in those examples, we can clearly see that failure to consider HLS factors has tremendous potential to produce bias in health research. One possibility that I proposed was that personality might account for the HLS, and provide for a parsimonious correction of biases resulting from the HLS. The results I have reported demonstrate that personality traits do not account for enough of the HLS to completely correct for these biases. They do, however, explain a large portion of the variance of the HLS. So much that interventions aimed at fostering HLS factors in the hopes of bringing about changes in public health could benefit from incorporating personality, and may suffer greatly by ignoring it.

In the three studies reported here, the effects of personality were not fully mediated by the HLS. In most cases, personality had effects on health that were still not accounted for. Other pathways may convey these effects from personality to health. This suggests that personality has effects on health that are yet to be clearly elucidated, and which have not yet been incorporated into epidemiological models of health.

Alternatively, personality and health may have corresponsive relationships. In this case, any effects on personality emanating from health might not be subsumed by an obvious mediator. In either case, the paths linking personality and health offer new horizons for understanding health processes.

Future Directions

Modeling the HLS as a latent variable provides new avenues for understanding the effects of multiple health factors on health. The large association between the HLS and health is consistent with the hypothesis that a single health factor could pick up extra predictive validity resulting from other causal factors. If the HLS is correctly specified and does not continue to gain in predictive validity when adding other health factors, researchers could estimate a latent HLS variable, enter it into a model, and attempt to account for this source of spurious relationships. If the assumptions I have just described hold, this latent variable would adequately account for unmeasured effects that would normally operate through the HLS. In effect, controlling for the HLS would subsume the effects of numerous potential confounds. The models presented here allow for just such a scenario to be tested. Estimating the HLS as a latent variable and employing it in SEM models provides a framework for more accurately evaluating single health factors as predictors of health outcomes. Fitting bi-factor SEM models will allow researchers to evaluate the unique effect of any one factor after partialling out the effect of the HLS.

Personality traits are important for predicting health outcomes, and for understanding health processes. Perhaps the most important finding reported here is that the effects of conscientiousness and neuroticism operate partially through the HLS, but also have validity with respect to health that operates outside of the HLS. This has two implications for epidemiological research: 1) Future research involving the HLS and health would benefit greatly from the inclusion of personality traits as part of an explanatory model for how HLS factors operate on health, and 2) Personality traits also offer extra prediction of health which operates through other mechanisms outside of the HLS. These other pathways could include physiological, social cognitive, developmental, or as yet unarticulated social environmental factors. This represents an opportunity for epidemiological and heath researchers to discover novel pieces of the health process across the lifespan. It also points to a large area of as yet unexplained effects in epidemiological research. For example, mean levels of personality traits have been shown to vary across states (Rentfrow, Gosling, & Potter, 2008). These mean level differences may be partially responsible for varying incidences of specific health outcomes across geographical locations. At the broadest level, statewide personality differences could help to explain effects ranging from the efficacy of public health interventions to variations in the quality of care across municipalities.

The covariance of health factors that constitutes the HLS and the association of the HLS with personality present a new perspective on health behavior change. While recent work on multiple health behavior change has recognized that some health related factors covary and need to be considered together (Prochaska et al., 2008), theories of health behavior change have not adequately integrated personality. There are multiple places in the health behavior change process where personality could come into play. As a pre-morbid risk factor, personality assessments can be used to identify people who are at greater risk of multiple negative health outcomes. It may be possible to target health interventions to those individuals. Personality traits may also come into play in determining how individuals will construe health behavior interventions, and the degree to which certain types of interventions are likely to succeed. For example individuals high on conscientiousness may be more likely to respond positively to a health behavior intervention, and may be more apt to maintain a new health regime over time. Individuals who are lower on conscientiousness may require more salient rewards to motivate them to change, and may also require more instrumental support in adhering to a new set of behaviors. Finally, personality traits may provide paths for direct intervention if they have effects on health that are independent of health behaviors.

Limitations

Does BMI fit in the HLS?

Definitions of the HLS consistently identify social environmental factors, health behaviors, and BMI as the core components of the HLS. While BMI can be thought of as a behavioral indicator of one's propensity to maintain a healthy weight, it is often used as an indicator of physical health. The more common treatment of BMI as a health indicator is best exemplified by research on metabolic syndrome (Hillier et al., 2006). When operating as a heath behavior indicator, BMI is viewed as the result of weight related health behaviors.

My treatment of BMI results from the fact that the HLS is rarely mentioned without BMI being invoked as one of its components. I treated BMI with special care since it could easily be thought of as an indicator of either the HLS or physical health. I tested models that used BMI in both ways, and also compared these models to ones that did not include BMI at all. In two of the three studies, removing BMI from an HLS CFA did improved model fit, while in the third, it did not. In models that tested the latent correlation between BMI and health, removing BMI improved model fit. In order to ensure that this was a fair comparison I also looked at models that removed an unassailable HLS indicator; tobacco consumption. Removing tobacco consumption similarly improved fit in two of my three samples, suggesting that part of the improvement in fit may have resulted from achieving a favorable balance in the number of paths to be estimated and the number of indicators employed in the model.

Models that employed BMI as an indicator of physical health resulted in very similar findings to those that did not include BMI at all. Across all three studies, the best model fit was achieved by allowing BMI to load on both health and the HLS. However when taken all together, model fit does not provide a compelling and clear rational for one treatment of BMI over all others. Taking the latent correlation between the HLS and health as a criterion for determining the most appropriate model is less equivocal. Models that include BMI as an indicator for the HLS consistently produced the largest latent correlation. Furthermore, none of these models taken separately were inherently poorly fitting. While recognizing that BMI may be different from other HLS indicators, I would argue that these results do not suggest that including BMI as a HLS indicator is destructive to the HLS construct, or statistically questionable with respect to physical health. Additionally, the consistently larger latent correlation between the HLS and health suggest that this scenario allows BMI to provide the most valid information.

Subjective Heath and the HLS

Self-reported health and the HLS had medium to large correlations across all three studies. In each study physical health was estimated using multiple health indicators. Ideally, estimating health based on a combination of global self-ratings, functional aspects of health, and self-reported pain would result in a latent variable that is less subject to any one source of bias. Nevertheless this outcome may be criticized since it is constructed entirely from self-reported health items. In the face of such concerns, it is important to realize that self-reported health measures have an established and consistent relationship with mortality (Idler & Benyamini, 1997). This places self-reported health in good company with other subjective variables which predict objective outcomes. For example, observer ratings of perceived age based on photographs are subjective in contrast to actual chronological age. Despite their subjective component, such ratings are predictive of mortality above and beyond both chronological age, and previously established biomarkers of age such as telomere length. The predictive validity of perceived age is consistent across raters of different ages and backgrounds (Christensen et al., 2009).

Common criticisms of subjective measures rest on the notion that they are subject to systematic biases. Instances where subjective measures have predictive validity despite this possibility demonstrate that subjective ratings are not synonymous with low validity. In some cases subjective ratings may represent nuanced judgments based on well-honed heuristic systems, which optimally balance multiple sources of information (Diener, Lucas, Schimmack, & Helliwell, 2008; Vazire, 2010). These two perspectives, while at odds, are not mutually exclusive. I would argue that both scenarios are at play. Subjective ratings of health are nuanced judgments, which weigh multiple sources of information. They are also subject to potential bias. The fact that subjective health is a consistently strong predictor of mortality suggests that, whatever biases typically occur in these ratings, they are not so great as to render measures of self-rated health meaningless.

Short Measures, Internal Consistency, and Big Five Facets

One recurring theme in these analyses is that not all trait measures cover the same content. This is especially true of short measures. When short measures are constructed using classical test construction techniques, it is very likely that the items selected will necessarily focus on a very narrow aspect of the construct being measured. This is typically the only way to achieve acceptable alpha reliability with just a few items. Unfortunately, this approach to measuring the Big Five quickly fails to capture the breadth of Big Five trait domains.

Longer trait measures are not immune to this problem. In the case of conscientiousness, there is no single widely used inventory that captures all of the replicable facets of the construct (Jackson et al. 2009). However, when using measures that narrowly tap one facet, researchers run the risk of being left with a facet that may not be related to the outcome of interest. Of the three studies, the GSOEP results stand out as being the least consistent with the other three. It is also the data set with the shortest Big Five scales; each factor is estimated with only three items. The field of personality research is fortunate to have so many large scale studies such as the HRS and the GSOEP incorporating personality measures. As much as we might like to have fully elaborated broad measures of the Big Five available in these samples, it is far more likely that shorter measures will be employed, simply due to logistic limitations inherent in such broadly construed studies. Given this reality, researchers using short personality measures must be aware of the facet level structure of Big Five domains. This is necessary for researchers to have the capacity to recognize which aspects of a trait they are measuring, and what measurement trade-offs are being made. Failing to do so runs the risk of diluting the predictive power of personality measures, and in turn giving a misleading representation of the value of personality for predicting outcomes in other domains.

Summary

The HLS fit well as a latent variable across all three samples. Personality traits account for a large portion of the variance in the HLS. Conscientiousness and neuroticism had the most consistent and sizeable relationships with the HLS and health. The HLS operated as partial or full mediator of the effects of personality on health.

These findings strongly support the inclusion of personality traits in models of health processes and epidemiological research. The present work provides a viable framework for multiple new research directions. Modeling the HLS as a latent variable provides new ways to model specific types of bias in epidemiological and health research. It also allows for more accurate estimation of the effects of single health factors. Pathways linking personality to health are not completely subsumed by the HLS. This suggests that there may be many as yet un-described paths linking personality to health. The established pathways linking personality to health demonstrate that personality can be incorporated into existing epidemiological perspectives and methodologies. Unaccounted for effects of personality on health observed in these three studies may have operated through physiological pathways, or through as yet unconsidered mechanisms. The finding that personality traits have predictive validity with respect to health distinct from the healthy lifestyle highlights that personality has the potential to push epidemiological research in new fruitful directions.

TABLES AND FIGURES

Figure 1. A model evaluating the HLS as a mediator of the effect of conscientiousness on physical health (PH).

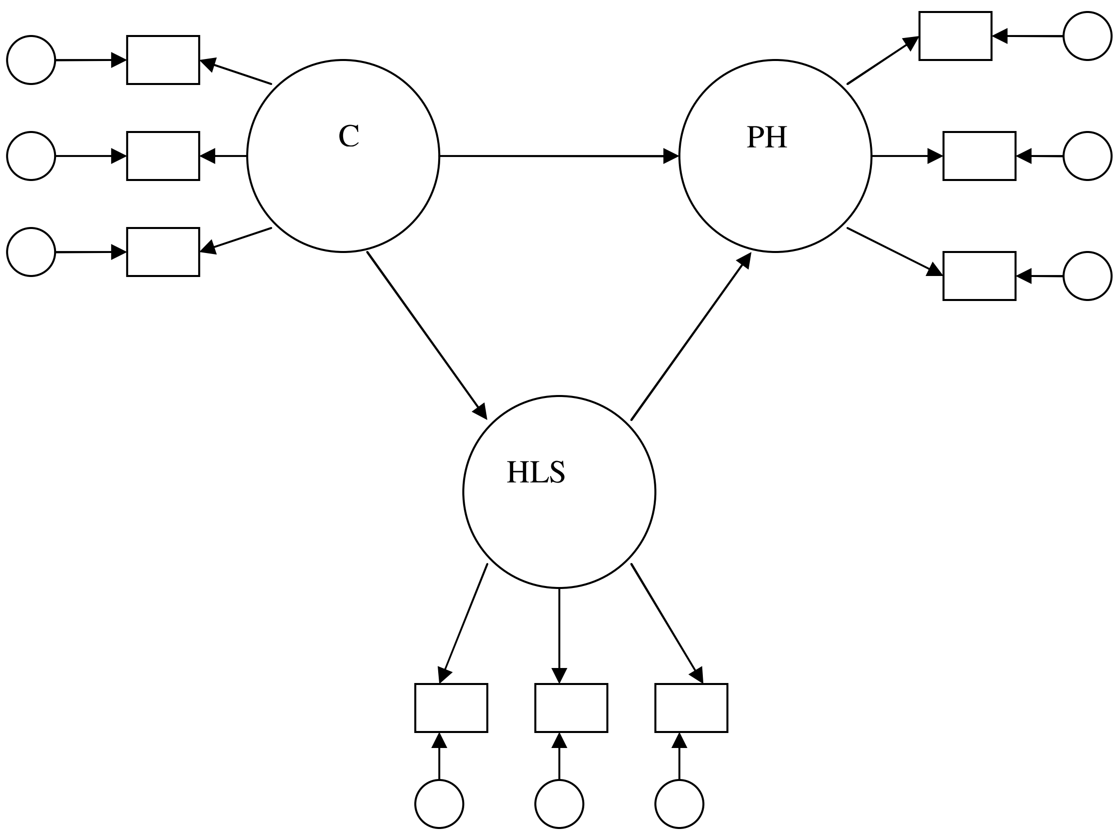

Table 1. HASCI: Five models designed to evaluate the suitability of BMI as an indicator of the HLS.

	Model 1	Model 2	Model 3	Model 4	Model 5
Latent *r*	.62	.54	.54	.53	.59
CFI	.91	.92	.92	.93	.92
RMSEA	.08	.09	.08	.08	.09
AIC	309.78	256.82	288.86	280.57	264.80
Chi Squared (df)	257.80 (18)	210.80 (12)	236.90 (18)	226.60 (17)	220.80 (13)

N=2136; Model 1 includes BMI in the HLS. Model 2 removes BMI entirely. Model 3 places BMI on health. Model 4 allows BMI to load on both health and the HLS. Model 5 includes BMI but removes tobacco consumption.

Table 2. HASCI: Big Five traits as single versus simultaneous predictors of physical health.

			Model fit Statistics for Single predictors			
Path	Single Predictors	Simultaneous Predictors	χ^2	df	CFI	RMSEA (90% CI)
Conscientiousness → Health	.34*	.22*	276.65	32	.98	.06 (.05-.07)
Neuroticism→ Health	-.30*	-.16*	255.48	32	.97	.06(.05-.06)
Intellect→Health	.30*	.16*	294.00	32	.96	.06(.06-.07)
Agreeableness→Health	.27*	.04	295.76	32	.97	.06(.06-.07)
Extraversion→Health	.21*	.13*	358.11	32	.95	.07(.06-.08)
Model Fit Statistics for full model:						
χ^2		3429.71				
df		284				
CFI		.90				
RMSEA		.07				

N = 2136; * p < .05; All models control for age and gender

Table 3. HASCI: Big Five traits and hostility as single versus simultaneous predictors of physical health.

			Model fit Statistics for Single predictors			
Path	Single Predictors	Simultaneous Predictors	χ^2	df	CFI	RMSEA (90% CI)
Conscientiousness → Health	.34*	.23*	276.65	32	.98	.06 (.05-.07)
Neuroticism→ Health	-.30*	-.13*	255.48	32	.97	.06(.05-.06)
Intellect→Health	.30*	.17*	294.00	32	.96	.06(.06-.07)
Hostility→Health	-.28*	-.07*	430.40	32	.96	.08(.07-.08)
Extraversion→Health	.21*	.13*	358.11	32	.95	.07(.06-.08)
Model Fit Statistics for full model:						
χ^2		3852.1				
df		284				
CFI		.90				
RMSEA		.08				

N = 2136; * p < .05; All models control for age and gender

Table 4. HASCI: Big Five traits and hostility as predictors of the HLS.

			Model fit Statistics for Single predictors			
Path	Single Predictors	Simultaneous Predictors	χ^2	df	CFI	RMSEA (90% CI)
Conscientiousness	.26*	.23*	332.9	40	.98	.06 (.05-.06)
Neuroticism	.16*	.08*	271.40	40	.95	.05(.04-.06)
Intellect	.70*		454.8	40	.88	.07(.06-.08)
Hostility	-.15*	-.04	463.8	40	.93	.07(.07-.08)
Extraversion	.12*	.14*	357.5	40	.89	.06(.06-.07)
Model Fit Statistics for full model:						
χ^2		3044.20				
df		217				
CFI		.89				
RMSEA		.08(.08-.08)				

N = 2136; * $p < .05$ All models control for age and gender

Table 5. HASCI: The HLS as a mediator of personality traits taken singly.

						Model fit Statistics			
Path	Model	Path A	Path B	Path C	Indirect effect(95%CI)	χ^2	df	CFI	RMSEA (90% CI)
Conscientiousness									
	Reduced	.27*	.00	.40*		922.43	70	.94	.08 (.07-.08)
	Full	.32*	.56*	.22*	.18(.11-.28)	675.30	69	.96	.06 (.06-.07)
Neuroticism									
	Reduced	-.20*	.00	-.43*		954.20	70	.88	.08(.07-.08)
	Full	-.23*	.57*	-.30*	-.13(.08-.20)	678.90	69	.92	.06(.06-.07)
Hostility									
	Reduced	-.19*	.00	-.48*		1132.90	70	.89	.08(.08-.09)
	Full	-.24*	.55*	-.34*	-.13(.07-.25)	853.00	69	.92	.07(.07-.08)
Extraversion									
	Reduced	.15*	.00	.22*		1139.80	70	.80	.08(.09-.09)
	Full	.18*	.61*	.10*	.11(.06-.16)	861.00	69	.85	.07(.07-.08)

N = 2136; * p < .05; All models control for age and gender

Table 6. HASCI: The HLS a simultaneous mediator of conscientiousness, neuroticism, hostility and extraversion on health.

						Model fit Statistics			
Path	Model	Path A	Path B	Path C'	Indirect effect(95%CI)	χ^2	df	CFI	RMSEA (90% CI)
Conscientiousness									
	Reduced	.23*	.00	.26*		3856.95	280	.88	.08 (.07-.08)
	Full	.25*	.53*	.13*	.14*(.08-.22)	3629.96	279	.89	.08 (.07-.08)
Neuroticism									
	Reduced	-.08*	.00	-.17*					
	Full	-.07*	.53*	-.14*	.04(-.02-.09)				
Hostility									
	Reduced	-.08*	.00	-.30*					
	Full	-.09*	.53*	-.25*	-.05(-.14-.01)				
Extraversion									
	Reduced	.16*	.00	.13*					
	Full	.14*	.53*	.06*	.07*(.03-.11)				

N = 2136; * $p < .05$; All models control for age and gender

Table 7. HASCI: The HLS as a simultaneous mediator of conscientiousness, neuroticism, and extraversion on health.

						Model fit Statistics			
Path	Model	Path A	Path B	Path C′	Indirect effect(95%CI)	χ^2	df	CFI	RMSEA (90% CI)
Conscientiousness									
	Reduced	.23*	.00	.26*		3856.95	280	.88	.08 (.07-.08)
	Full	.27*	.54*	.15*	.15*(.09-.24)	1921.00	193	.92	.07 (.06-.07)
Neuroticism									
	Reduced	-.08*	.00	-.17*					
	Full	-.11*	.54*	-.25*	.06*(.02-.11)				
Extraversion									
	Reduced	.16*	.00	.13*					
	Full	.14*	.54*	.07*	.08*(.04-.12)				

N = 2136; * p < .05; All models control for age and gender

Table 8. HASCI: The HLS as a simultaneous mediator of the effects of conscientiousness, hostility, and extraversion on health.

						Model fit Statistics			
Path	Model	Path A	Path B	Path C′	Indirect effect(95%CI)	χ^2	df	CFI	RMSEA (90% CI)
Conscientiousness									
	Reduced	.24*	.00	.29*		2267.37	194	.91	.07 (.07-.07)
	Full	.26*	.52*	.15*	.26*(.19-.36)	2039.41	193	.92	.07 (.06-.07)
Hostility									
	Reduced	-.10*	.00	-.37*					
	Full	-.12*	.52*	-.31*	-.09*(.-19 - -.03)				
Extraversion									
	Reduced	.16*	.00	.13*					
	Full	.14*	.52*	.06*	.13*(.07-.20)				

N = 2136; * p < .05; All models control for age and gender

Table 9. GSOEP: Latent correlations between HLS and health across four models.

	BMI on HLS	BMI removed	BMI on Health	BMI on health and HLS	Tobacco Removed
Latent *r*	.34	.32	.25	.29	.35
CFI	.92	.94	.94	.96	.94
RMSEA	.07	.07	.07	.06	.07
AIC	732.68	541.60	502.32	392.30	510.74
Chi Squared (df)	682.70 (19)	497.6 (13)	458.30 (13)	346.3 (12)	466.7 (13)

N=7732; Model 1 includes BMI in the HLS. Model 2 removes BMI entirely. Model 3 places BMI on health. Model 4 allows BMI to load on both health and the HLS. Model 5 includes BMI but removes tobacco consumption.

Table 10. GSOEP: Big Five traits as single versus simultaneous predictors of physical health.

			Model fit Statistics for Single predictors			
Path	Single Predictors	Simultaneous Predictors	χ^2	df	CFI	RMSEA (90% CI)
Conscientiousness → Health	.12*	.06*	434.80	17	.96	.06 (.05-.06)
Neuroticism→ Health	-.34*	-.32*	464.70	17	.96	.06(.05-.06)
Intellect→Health	.15*	.07*	717.20	17	.94	.07(.07-.08)
Agreeableness→Health	.09*	.00	189.3	17	.98	.04(.03-.04)
Extraversion→Health	.16*	.06*	337.90	17	.97	.05(.05-.05)
Model Fit Statistics for full model:						
χ^2		9762.40				
df		155				
CFI		.71				
RMSEA		.09(.09-.09)				

N = 7732; * $p < .05$; All models control for age and gender

Table 11. GSOEP: Big Five traits and as predictors of the HLS.

			Model fit Statistics for Single predictors			
Path	Single Predictors	Simultaneous Predictors	χ^2	df	CFI	RMSEA (90% CI)
Conscientiousness	.17*	.12*	2078.90	32	.71	.09 (.09-.09)
Neuroticism	-.08*	-.05*	1891.71	32	.71	.09(.08-.09)
Intellect	.31*	.28*	2492.93	32	.67	.10(.10-.10)
Extraversion	.14*	-.01	1936.45	32	.75	.09(.08-.09)
Model Fit Statistics for full model:						
χ^2		8370.95				
df		140				
CFI		.65				
RMSEA		.09(.09-.09)				

N = 7732; * $p < .05$ All models control for age and gender

Table 12. GSOEP: Big Five traits and as predictors of the HLS.

			Model fit Statistics for Single predictors			
Path	Single Predictors	Simultaneous Predictors	χ^2	df	CFI	RMSEA (90% CI)
Conscientiousness	.18*	.09*	393.35	19	.93	.05 (.05-.06)
Neuroticism	-.08*	-.04*	369.81	19	.91	.05(.05-.05)
Intellect	.35*	.32*	559.92	19	.89	.06(.06-.07)
Extraversion	.19*	.03	315.89	19	.95	.05(.04-.05)
Model Fit Statistics for full model:						
χ^2		6093.6				
df		115				
CFI		.71				
RMSEA		.08(.08-.08)				

N = 7732; * $p < .05$

Table 13. GSOEP: The HLS as a mediator of personality traits taken singly.

						Model fit Statistics			
Path	Model	Path A	Path B	Path C	Indirect effect(95%CI)	χ^2	df	CFI	RMSEA (90% CI)
Conscientiousness									
	Reduced	.19*	.00	.11*		1436.90	42	.88	.07 (.06-.07)
	Full	.13*	.34*	.06*	.04*(.03-.06)	1109.64	41	.91	.06 (.06-.06)
Neuroticism									
	Reduced	-.16*	.00	-.38*		1522.10	42	.87	.07(.07-.07)
	Full	-.12*	.31*	-.33*	-.04*(-.02- -.05)	1182.60	41	.91	.06(.06-.06)
Intellect									
	Reduced	.38*	.00	.24*		1549.20	42	.87	.07(.07-.07)
	Full	.33*	.31*	.11*	.11*(.09-.12)	1296.30	41	.89	.06(.06-.07)
Extraversion									
	Reduced	.21*	.00	.19*		1348.14	42	.90	.06(.06-.07)
	Full	.18*	.32*	.12*	.06*(.05-.07)	1007.28	41	.91	.06(.05-.06)

N = 7732; * p < .05;

Table 14. GSOEP: The HLS as a simultaneous mediator of the effects of conscientiousness, neuroticism, and intellect on health.

						Model fit Statistics			
Path	Model	Path A	Path B	Path C′	Indirect effect(95%CI)	χ^2	df	CFI	RMSEA (90% CI)
Conscientiousness									
	Reduced	.08*	.00	.03		4161.74	113	.81	.07(.07-.07)
	Full	.05*	.30*	.01	.02(.08-.22)	3924.07	112	.82	.07(.07-.07)
Neuroticism									
	Reduced	-.12*	.00	-.35*					
	Full	-.08*	.30*	-.32*	-.02(.04- .01)				
Intellect									
	Reduced	.35*	.00	.20*					
	Full	.31*	.30*	.08*	.09(.08-.11)				

N = 7732; * p < .05

Table 15. HRS: Latent correlation between HLS and health when BMI is included, removed, or used as an indicator on health.

	BMI on HLS	BMI removed	BMI on Health	BMI on health and HLS	Tobacco Removed
Latent *r*	.92	.82	.82	.82	.92
CFI	.94	.96	.94	.95	.96
RMSEA	.06	.05	.05	.05	.06
AIC	263.34	161.41	243.07	240.74	183.81
Chi Squared (df)	219.30 (13)	123.4(8)	199.10(13)	194.70(12)	145.8(8)

N=5193; Model 1 includes BMI in the HLS. Model 2 removes BMI entirely. Model 3 places BMI on health. Model 4 allows BMI to load on both health and the HLS. Model 5 includes BMI but removes tobacco consumption.

Table 16. HRS: Big Five traits as single versus simultaneous predictors of physical health.

			Model fit Statistics for Single predictors			
Path	Single Predictors	Simultaneous Predictors	χ^2	df	CFI	RMSEA (90% CI)
Conscientiousness → Health	.39*	.35*	487.40	24	.90	.06(.06-.07)
Neuroticism→ Health	-.35*	-.27*	568.90	24	.92	.07(.06-.07)
Intellect→Health	.17*	.02	446.20	24	.94	.06(.05-.06)
Agreeableness→Health	.12*	-.14*	379.30	24	.95	.05(.05-.06)
Extraversion→Health	.23*	.14*	438.20	24	.94	.06(.05-.06)
Hostility→Health	-.26*	-.19*	264.90	24	.97	.04(.04-.05)
Model Fit Statistics for full model:						
χ^2		11700.30				
df		359				
CFI		.70				
RMSEA		.08(.08-.08)				

N = 5193; * p < .05; All models control for age and gender

Table 17. HRS: Big Five traits and hostility as predictors of the HLS.

			Model fit Statistics for Single predictors			
Path	Single Predictors	Simultaneous Predictors	χ^2	df	CFI	RMSEA (90% CI)
Conscientiousness	.43*	-.37*	1009.50	32	.72	.08 (.07-.08)
Neuroticism	-.31*	-.20*	1000.92	33	.81	.08(.07-.08)
Agreeableness	.00		744.90	32	.92	.06(.06-.07)
Extraversion	.14*	.03	1936.45	32	.75	.09(.08-.09)
Hostility	-.45	-.40*	856.07	32	.87	.07(.07-.08)
Model Fit Statistics for full model:						
χ^2		4388.73				
df		197				
CFI		.78				
RMSEA		.06(.06-.07)				

N = 5913; * p < .05 All models control for age and gender

Table 18. HRS: The HLS as a mediator of personality traits taken singly.

						Model fit Statistics			
Path	Model	Path A	Path B	Path C	Indirect effect(95%CI)	χ^2	df	CFI	RMSEA (90% CI)
Conscientiousness									
	Reduced	.60*	.00	.50*		2039.5	59	.72	.08 (.08-.08)
	Full	.47*	.94*	.05	.45*(.36-.56)	1473.40	58	.80	.07 (.07-.07)
Neuroticism									
	Reduced	-.37*	.00	-.38*		2289.49	59	.74	.09(.08-.09)
	Full	-.28*	.88*	-.10*	-.25*(-.31- -.20)	1605.23	58	.82	.07(.06-.07)
Hostility									
	Reduced	-.49*	.00	-.36*		1715.30	59	.78	.07(.07-.08)
	Full	-.46*	1.05*	-.20*	-.51*(-.43- -.64)	1050.40	58	.87	.06(.05-.06)
Extraversion									
	Reduced	.23*	.00	.27*		2175.30	59	.73	.08(.08-.09)
	Full	.17*	.92*	.09*	.16*(.12-.21)	1370.80	58	.83	.07(.06-.07)

N = 5193; * $p < .05$; All models control for age and gender

Table 19. The HLS a simultaneous mediator of the effects of conscientiousness, neuroticism, and hostility on health.

						Model fit Statistics			
	Model	Path A	Path B	Path C'	Indirect effect(95%CI)	χ^2	df	CFI	RMSEA (90% CI)
Conscientiousness									
	Reduced	.49*	.00	.41*		3483.62	175	.82	.06(.06-.06)
	Full	.42*	1.00*	.07	.42*(.31-.60)	3065.68	174	.84	.06(.06-.06)
Neuroticism									
	Reduced	-.22*	.00	-.29*					
	Full	-.18*	1.00*	-.10*	-.18*(-.12- -.27)				
Hostility									
	Reduced	-.42*	.00	-.21*					
	Full	-.41*	1.00*	.22*	-.41*(-.59- -.32)				

N = 5193; * $p < .05$

REFERENCES

Adler, N. & Matthews, K. (1994). Health Psychology: Why do some people get sick and some stay well? *Annual Review of Psychology, 45,* 229-259.

Adler, N., Singh-Manoux, A., Schwartz, J., Stewart, J., Matthews, K., & Marmot, M. G. (2008). Social status and health: a comparison of British civil servants in Whitehall-II with European-and African-Americans in CARDIA. *Social Science & Medicine*, *66*, 1034–1045.

Albert, C. M., Gaziano, J. M., Willett, W. C., Manson, J. E. (2002). Nut consumption and decreased risk of sudden cardiac death in the Physicians' Health Study, *Archives of internal medicine, 162*, 1382-1387.

Allison, D. B., Fontaine, K. R., Manson, J. A., Stevens, J., & VanItallie, T. B. (1999). Annual deaths attributable to obesity in the United States. *Jama*, *282*, 1530-1538.

Anderson, C., John, O. P., Keltner, D., & Kring, A. M. (2001). Who attains social status? Effects of personality and physical attractiveness in social groups. *Journal of Personality and Social Psychology*, *81*, 116–132.

Barefoot, J. C., Dahlstrom, W. G., & Williams, R. B. (1983). Hostility, CHD incidence, and total mortality: a 25-year follow-up study of 255 physicians. *Psychosomatic Medicine*, *45*, 59-63.

Baron, K. G., Smith, T. W., Butner, J., Nealey-Moore, J., Hawkins, M. W., & Uchino, B. N. (2006). Hostility, Anger, and Marital Adjustment: Concurrent and Prospective Associations with Psychosocial Vulnerability. *Journal of Behavioral Medicine*, *30*, 1-10.

Barrett-Connor, E., & Grady, D. (1998).Hormone replacement therapy, heart disease, and other considerations. *Annual Review of Public Health*, *19*, 55–72.

Birmingham, W., Uchino, B. N., Smith, T., Light, K. C., & Sanbonmatsu, D. M. (2009). Social ties and cardiovascular function: An examination of relationship positivity and negativity during stress. *International Journal of Psychophysiology*, *74*, 114–119.

Bogg, T., & Roberts, B. W. (2004). Conscientiousness and health-related behaviors: A meta-analysis of the leading behavioral contributors to mortality. *Psychological Bulletin*, *130*, 887–919.

Bolger, N., & Zuckerman, A. (1995). A framework for studying personality in the stress process. *Journal of Personality and Social Psychology*, *69*, 890–890.

Bosetti, C., Spertini, L., Parpinel, M., Gnagnarella, P., Lagiou, P., Negri, E., Franceschi, S., et al. (2005). Flavonoids and breast cancer risk in Italy. *Cancer Epidemiology Biomarkers & Prevention*, *14*, 805.

Booth-Kewley, S. & Vickers, R. R. (1994).Associations between major domains of personality and health behavior. *Journal of Personality, 62,* 281–298.

Brookhart, M. A., Patrick, A. R., Dormuth, C., Avorn, J., Shrank, W., Cadarette, S. M., & Solomon, D. H. (2007). Adherence to lipid-lowering therapy and the use of preventive health services: an investigation of the healthy user effect. *American Journal of Epidemiology*, *166*, 348-354.

Buss, A.H., & Warren, W. L. (2000) *The Aggression Questionnaire manual*, Los Angeles CA: Western Psychological Services.

Caspi, A., Begg, D., Dickson, N., Harrington, H.L., Langley, J., Moffitt, T.E., & Silva, P.A. (1997). Personality traits predict health-risk behaviors. *Journal of Personality and Social Psychology, 73,* 1052-1063.

Chang, P. P., Ford, D. E., Meoni, L. A., Wang, N. Y., & Klag, M. J. (2002). Anger in young men and subsequent premature cardiovascular disease: the precursors study. *Archives of Internal Medicine*, *162*, 901-906.

Chapman, B. P., Fiscella, K., Kawachi, I., & Duberstein, P. R. (2010). Personality, Socioeconomic Status, and All-Cause Mortality in the United States. *American Journal of Epidemiology, 171*, 83-92.

Chapman, B. P., Shah, M., Friedman, B., Drayer, R., Duberstein, P. R., Lyness, J. M. (2009). Personality traits predict emergency department utilization over three years in older patients. *American Journal of Geriatric Psychiatry, 17,* 526–535.

Chiolero, A., Faeh, D., Paccaud, F., & Cornuz, J. (2008). Consequences of smoking for body weight, body fat distribution, and insulin resistance1, 2. *American Journal of Clinical Nutrition*, *87*, 801–809.

Chiuve, S. E. (2006). Healthy Lifestyle Factors in the Primary Prevention of Coronary Heart Disease Among Men: Benefits Among Users and Nonusers of Lipid-Lowering and Antihypertensive Medications. *Circulation*, *114*, 160-167.

Chiuve, S. E., Rexrode, K. M., Spiegelman, D., Logroscino, G., Manson, J. E., & Rimm, E. B. (2008). Primary Prevention of Stroke by Healthy Lifestyle. *Circulation*, *118*, 947-954.

Concato J., Shah N., Horwitz, R. I. (2000). Randomized, controlled trials, observational studies, and the hierarchy of research designs. *New England Journal of Medicine, 342,* 1887–92.

Coronary Drug Project Research Group. (1980) Influence of adherence to treatment and response of cholesterol on mortality in the coronary drug project. *New England Journal of Medicine, 303,* 1038–41.

Christensen, K., Thinggaard, M., McGue, M., Rexbye, H., Hjelmborg, J. V.B., Aviv, A., Gunn, D., van der Ouderaa, F., Vaupel, J.W. (2009). Perceived age as clinically useful biomarker of ageing: cohort study. *British Medical Journal, 339,* b5262.

Davila, J., Bradbury, T. N., Cohan, C. L., & Tochluk, S. (1997). Marital functioning and depressive symptoms: Evidence for a stress generation model. *Journal of Personality and Social Psychology*, *73*, 849–861.

Diener, E., Kesebir, P., Lucas, R. (2008). Benefits of accounts of well-being for societies and for psychological science. *Applied Psychology, 57,* 37-53.

Donnellan MB, Oswald FL, Bard BM, Lucas RE. (2006). The Mini-IPIP scales: Tiny-yet-effective measures of the big five factors of personality. Psychological Assessment, 18, 192-203.

Dormuth, C. R., Patrick, A. R., Shrank, W. H., Wright, J. M., Glynn, R. J., Sutherland, J., & Brookhart, M. A. (2009). Statin adherence and risk of accidents: A cautionary tale. *Circulation*, *119*, 2051-2057.

Everson, S. A., Kauhanen, J., Kaplan, G. A., Goldberg, D., E., Julkunen, J., Tuomilehto, J., & T. Salonen, J., T. (1997). Hostility and Increased Risk of Mortality and Acute Myocardial Infarction: The Mediating Role of Behavioral Risk Factors. *American Journal of Epidemiology, 146,* 142-152.

Filakti, H., & Fox, J. (1995). Differences in mortality by housing tenure and car ownership. *Population Trends, 81,* 27-30.

Friedman, H. S., Tucker, J. S., Tomlinson-Keasey, C., Schwartz, J. E., Wingard, D. L., & Criqui, M. H. (1993). Does childhood personality predict longevity? *Journal of Personality and Social Psychology*, *65*, 176–176.

Gaesser, G. A. (2003). Is it necessary to be thin to be healthy? *Harvard Health Policy Review*, *4*, 40–47.

Garbe, E., & Suissa, S. (2004). Issues to debate on the Women's Health Initiative (WHI) study: Hormone replacement therapy and acute coronary outcomes: methodological issues between randomized and observational studies. *Human Reproduction*, *19*, 8-13.

Gerrard, M., Gibbons, F. X., Stock, M. L., Houlihan, A. E., Dykstra, J. L. (2006). Temperament, self-regulation, and the Prototype Willingness Model of adolescent health risk behavior. In D. T. D. de Ridder & J. B. F. de Wit (Eds.) *Self-regulation in health behavior* (pp. 97-117).Chichester, England: Wiley & Sons.

Giles, L. C., Glonek, G. F. V., Luszcz, M. A., Andrews, G. R. (2005). Effect of social networks on 10 year survival in very old Australians: the Australian longitudinal study of aging. *Journal of Epidemiology and Community Health, 59,* 574-579.

Goldberg, L. R. (1999). A broad-bandwidth, public domain, personality inventory measuring the lower-level facets of several five-factor models. In I. Mervielde, I. Deary, F. De Fruyt, & F. Ostendorf (Eds.), Personality psychology in Europe (Vol. 7, pp. 7–28). Tilburg, the Netherlands: Tilburg University Press.

Golden J., Conroy R. M., Lawlor B. A. (2009). Social support network structure in older people: underlying dimensions and association with psychological and physical health. *Psychology Health and Medicine, 14,* 280-90.

Grodstein, F., & Stampfer, M. J. (1998). Estrogen for women at varying risk of coronary disease. *Maturitas*, *30*, 19–26.

Hagoel, L., Ore, L., Neter, E., Silman, Z., & Rennert, G. (2002). Clustering Women's Health Behaviors. *Health Education & Behavior*, *29*, 170-182.

Hampson, S. E., Andrews, J. A., Barckley, M., & Severson, H. H. (2006). Personality Predictors of the Development of Elementary-School Children's Intentions to Drink Alcohol: The Mediating Effects of Attitudes and Subjective Norms. *Psychology of Addictive Behaviors*, *20*, 288-297.

Hampson, S. E., Goldberg, L. R., Vogt, T. M., & Dubanoski, J. P. (2007). Mechanisms by which childhood personality traits influence adult health status: Educational attainment and healthy behaviors. *Health Psychology, 26*, 121-125.

Hillier, T. A., Rousseau, A., Lange, C., Lepinay, P., Caileau, M., Novak, M., Calliez, E., Ducimetiere, P., & Balkau, B. (2006). Practical way to assess metabolic syndrome using a continuous score obtained from principle components analysis. *Diabetologia, 49,* 1528-1535.

Heckman, J. J. (2007). The economics, technology, and neuroscience of human capability formation. *Proceedings of the National Academy of Sciences*, *104*, 13250-13255.

Hofstee, W. K. B., de Raad, B., & Goldberg, L. R. (1992). Integration of the big five and circumplex approaches to trait structure. *Journal of Personality and Social Psychology, 63,* 146-163.

Holt-Lunstad, J., Uchino, B. N., Smith, T. W., & Hicks, A. (2007). On the importance of relationship quality: The impact of ambivalence in friendships on cardiovascular functioning. *Annals of Behavioral Medicine*, *33*, 278–290.

Holt-Lunstad, J., Smith, T. W., & Uchino, B. N. (2008). Can hostility interfere with the health benefits of giving and receiving social support? The impact of cynical hostility on cardiovascular reactivity during social support interactions among friends. *Annals of Behavioral Medicine*, *35*, 319-330.

House J. S., Landis K. R., & Umberson D. (1988). Social relationships and health. *Science, 241,* 540–545.

Houston, B. K., & Vavak, C. R. (1991). Hostility: Developmental factors, psychosocial correlates, and health behaviors. *Health Psychology, 10,* 9-17.

Hoyle, R. H., Fejfar, M. C., & Miller, J. D. (2000). Personality and sexual risk taking: A quantitative review. *Journal of Personality, 68,* 1203–1231.

Hu, F. B., Stampfer, M. J., Manson, J. A., Rimm, E. B., Colditz, G. A., Rosner, B. A., & Willett, W. C. (1998). Frequent nut consumption and risk of coronary heart disease in women: prospective cohort study. *British Medical Journal*, *317*, 1341-1345.

Hung, H. C., Joshipura, K. J., Jiang, R., Hu, F. B., Hunter, D., Smith-Warner, S. A., & Willet, W. C. (2004).Fruit and vegetable intake and risk of major chronic disease. *Journal of the National Cancer Institute*, *96*, 1577-1584.

Idler, E. L., Benyamini, Y. (1997). Self-Rated Health and Mortality: A Review of Twenty-Seven Community Studies. *Journal of Health and Social Behavior, 38*, 21-37.

Ironson, G.H., O'Cleirigh, C., Schneiderman, N., Weiss, A., Costa, P.T., (2008). Personality and HIV Disease Progression: Role of NEO-PI-R Openness, Extraversion, and Profiles of Engagement. *Psychosomatic Medicine, 70,* 245-253.

Jackson, J. J., Bogg, T., Walton, K., Wood, D., Harms, P. D., Lodi-Smith, J. L., & Roberts, B. W. (2009). Not all conscientiousness scales change alike: A multi-method, multi-sample study of age differences in the facets of conscientiousness. *Journal of Personality and Social Psychology, 96*, 446-459.

Jessor, R., & Jessor, S.L. (1997). Problem Behavior and Psychosocial Development: A Longitudinal Study of Youth. New York: Academic Press.

Jiao, L., Mitrou, P. N., Reedy, J., Graubard, B. I., Hollenbeck, A. R., Schatzkin, A., & Stolzenberg-Solomon, R. (2009). A combined healthy lifestyle score and risk of pancreatic cancer in a large cohort study. *Archives of Internal Medicine*, *169*, 764-770.

John, O.P., & Srivastava, S. (1999). The Big Five Trait taxonomy: History, measurement, and theoretical perspectives. In L.A. Pervin & O. P. John (Eds.), *Handbook of personality: Theory and research* (2nd ed., pp. 102–138). New York: Guilford Press.

Judge, T.A., Higgins, C.A., Thoresen, C.J., & Barrick, M.R. (1999).The big five personality traits, general mental ability, and career success across the life span. *Personnel Psychology, 52,* 621–652.

Kelly, E., & Conley, J. (1987). Personality and compatibility: A prospective analysis of marital stability and marital satisfaction. *Journal of Personality and Social Psychology, 52,* 27–40.

Karney, B. R., & Bradbury, T. N. (1997). Neuroticism, marital interaction, and the trajectory of marital satisfaction. *Journal of Personality and Social Psychology*, *72*, 1075–1092.

Lachman, M.E., & Weaver, S.L. (1997).*The Midlife Development Inventory (MIDI) personality scales: Scale construction and scoring.* Waltham, MA: Brandeis University.

Lemos-Giráldez, S., & Fidalgo-Aliste, A. M. (1997). Personality dispositions and health related habits and attitudes: A cross-sectional study. *European Journal of Personality, 11,* 197–209.
Little, T. D., Cunningham, W. A., Shahar, G., & Widaman, K. F. (2002). To parcel or not to parcel: Exploring the question, weighing the merits. *Structural Equation Modeling, 9,* 151-173.
Litwin, H., & Shiovitz-Ezra, S. (2006). Network type and mortality risk in later life. *The Gerontologist*, *46*, 735-743.
Lodi-Smith, J.L. & Roberts, B.W. (2007). Social Investment and Personality: A meta-analytic analysis of the relationship of personality traits to investment in work, family, religion, and volunteerism. *Personality and Social Psychology Review, 11,* 68-86.
Lund, R. (2004). Marital history from age 15 to 40 years and subsequent 10-year mortality: a longitudinal study of Danish males born in 1953. *International Journal of Epidemiology*, *33*, 389-397.
Matthews, K. A., Kuller, L. H., Wing, R. R., Meilahn, E. N., & Plantinga, P. (1996). Prior to use of estrogen replacement therapy, are users healthier than nonusers? *American Journal of Epidemiology*, *143*, 971-978.
Matthews, K. A. (2003). Hostile Behaviors Predict Cardiovascular Mortality Among Men Enrolled in the Multiple Risk Factor Intervention Trial. *Circulation*, *109*, 66-70.
McCann, S. E., Freudenheim, J. L., Marshall, J. R., & Graham, S. (2003). Risk of human ovarian cancer is related to dietary intake of selected nutrients, phytochemicals and food groups. *Journal of Nutrition*, *133*, 1937-1942.
Mokdad, A. H., Marks, J. S., & Stroup, D. F. (2004). Actual causes of death in the United States, 2000. *JAMA*, *29,*1238-1245.
Mroczek, D. K., Spiro, A., & Turiano, N. A. (2009). Do health behaviors explain the effect of neuroticism on mortality? Longitudinal findings from the VA Normative Aging Study. *Journal of Research in Personality, 43,* 653-659.
National Center for Chronic Disease Prevention and Health Promotion. (1999). YRBSS: Youth Risk Behavior Surveillance System.
National Center for Chronic Disease Prevention and Health Promotion. (2000). BRFSS: Behavioral Risk Factor Surveillance System.
Ostrove, J. M., Adler, N. E., Kuppermann, M., & Washington, A. E. (2000).Objective and subjective assessments of socioeconomic status and their relationship to self-rated health in an ethnically diverse sample of pregnant women. *Health Psychology*, *19,* 613–618.
Ozer, D. J., & Benet-Martínez, V. (2006).Personality and the prediction of consequential outcomes. *Annual Review of Psychology*, *57*, 401-421.
Petitti, D. B. (2005). Some surprises, some answers, and more questions about hormone therapy: further findings from the Women's Health Initiative. *JAMA*, *29*, 245-246.
Petitti, D. B., & Chen, W. (2008). Statistical adjustment for a measure of healthy lifestyle doesn't yield the truth about hormone therapy. In D. Nolan and T. Speed (Eds.),*Probability and Statistics: Essays in Honor of David A. Freedman*(pp.142-152),Beachwood, OH: Institute of Mathematical Statistics.
Preacher, K. J., & Hayes, A. F. (2004). SPSS and SAS procedures for estimating indirect effects in simple mediation models. *Behavior Research Methods, Instruments and Computers, 36,* 717-731.

Prentice, R. L., Langer, R., Anderson, G., & Barad, D. (2005). Prentice et al. Respond to" How Far Can Epidemiologists Get with Statistical Adjustment?" *American Journal of Epidemiology*, *162,* 419–420.

Prochaska, J. O., Butterworth, S., Redding, C. A., Buren, V., Perrin, N., Leo, M., Flaherty-Robb, M., Prochaska, J. M. (2007). Initial efficacy of MI, TTM tailoring, and HRI's with multiple behaviors for employee health promotion. *Preventive Medicine, 46,* 226-231.

Reeves, M. J., & Rafferty, A. P. (2005).Healthy lifestyle characteristics among adults in the United States, 2000.*Archives of Internal Medicine*, *165,* 854-857.

Rentfrow, P. J., Gosling, S. D. & Potter, J. (2008). A Theory of the Emergence, Persistence, and Expression of Geographic Variation in Personality Traits. *Perspectives on Psychological Science, 3,* 339-369.

Roberts, B. W., & Bogg, T. (2004). A 30-year longitudinal study of the relationships between conscientiousness-related traits, and the family structure and health-behavior factors that affect health. *Journal of Personality, 72,* 325-354.

Robins, R. W., Caspi, A., & Moffitt, T. E. (2000). Two personalities, one relationship: Both partners' personality traits shape the quality of their relationship. *Journal of Personality and Social Psychology*, *79*, 251–259.

Roberts, B. W., Caspi, A., & Moffitt, T. E. (2003). Work experiences and personality development in young adulthood. *Journal of Personality and Social Psychology*, *84,* 582–593.

Roberts, B. W., Kuncel, N. R., Shiner, R., Caspi, A., & Goldberg, L. R. (2007). The power of personality: The comparative validity of personality traits, socioeconomic status, and cognitive ability for predicting important life outcomes. *Perspectives on Psychological Science*, *2*, 313-345.

Roberts, B. W., Smith, J., Jackson, J. J., & Edmonds, G. W. (2009). Compensatory Conscientiousness and Health in Older Couples. *Psychological Science*, *20*, 553-559.
Robins, R. W., Caspi, A., & Moffitt, T. E. (2000). Two personalities, one relationship: Both partners' personality traits shape the quality of their relationship. *Journal of Personality and Social Psychology*, *79*, 251–259.
Samuelsson G., Dehlin, O. (1993). Family network and mortality: Survival chances through the lifespan of an entire cohort. *International Journal of Human Development, 137,* 277-295.

Saucier, G. (1994). Trapnell versus the Lexical Factor: More Ado About Nothing? *European Journal of Personality, 8,* 291-298.

Scherwitz L. W., Perkins L. L., Chesney M. A., Hughes G. H., Sidney S., & Manolio T. A. (1992). Hostility and health behaviors in young adults: The CARDIA study. Coronary artery risk development in young adults study. *American Journal of Epidemiology, 136*, 136–45.

Siegler, I. C. (1994). Hostility and risk: Demographic and lifestyle variables. In A. W. Siegman, & T. W. Smith (Eds.) *Anger, Hostility, and the Heart* (pp. 199-214). Hillsdale, NJ: Lawrence Erlbaum.

Simon, A. E., Steptoe, A., & Wardle, J. (2005). Socioeconomic status differences in coping with a stressful medical procedure. *Psychosomatic Medicine*, *67*, 270-276.

Smith, T. W. (1992). Hostility and health: Current status of a psychosomatic hypothesis. *Health Psychology*, *11*, 139–150.

Smith, T. W., & Gallo, L. C. (2001). Personality traits as risk factors for physical illness. In A. Baum, T. Revenson, & J. Singer (Eds.), *Handbook of health psychology* (pp. 139–172). Hillsdale, NJ: Lawrence Erlbaum.

Smith, T. W., Ruiz, J. M., & Gallo, L. C. (2004). Hostility, anger, aggressiveness, and coronary heart disease: An interpersonal perspective on personality, emotion, and health. Journal of Personality, 72, 1217-1270.

Spencer, C. A., Jamrozik, K., Norman, P. E., & Lawrence-Brown, M. (2005). A simple lifestyle score predicts survival in healthy elderly men. *Preventive Medicine*, *40*, 712–717.

Stampfer, M. J., Colditz, G. A. (1991). Estrogen replacement therapy and coronary heart disease: A quantitative assessment of the epidemiological evidence. *Preventative Medicine, 20,* 47-63.

Tamakoshi, A., Tamakoshi, K., Lin, Y., Yagyu, K., & Kikuchi, S. (2009). Healthy lifestyle and preventable death: Findings from the Japan Collaborative Cohort (JACC) Study. *Preventive Medicine*, *48*, 486–492.

Terracciano, A., & Costa, P. T. (2004). Smoking and the Five-Factor Model of personality. *Addiction*, *99*, 472-481.

Trobst, K. K., Herbst, J. H., Masters, H. L., & Costa, P. T. (2002). Personality pathways to unsafe sex: Personality, condom use, and HIV risk behaviors. *Journal of Research in personality*, *36*, 117–133.

Tucker, J. S., Friedman, H. S., Wingard, D. L., & Schwartz, J. E. (1996). Marital history at midlife as a predictor of longevity: Alternative explanations to the protective effect of marriage. *Health Psychology*, *15*, 94–101.

Tucker, J. S., Kressin, N. R., Spiro, A., & Ruscio, J. (1998). Intrapersonal characteristics and the timing of divorce: A prospective investigation. *Journal of Social and Personal Relationships, 15,* 211–225.

Tucker, J. S., Schwartz, J.E., Clark, K.M. & Friedman, H.S. (1999).Age-related changes in the association of social network ties with mortality risk. *Psychology and Aging, 14,* 564-571.

Turiano, N., & Mroczeck, D. (Under Review) *Openness to Experience and Mortality in Men: Analysis of Trait and Facet.*

Uchino, B.N., Smith, T.W., Hicks, A. (2007). On the Importance of Relationship Quality: The Impact of Ambivalence in Friendships on Cardiovascular Functioning. *Annals of Behavioral Medicine, 33,* 278-290.

US Department of Health and Human Services. (1996). *Physical Activity and Health: A Report of the Surgeon General.* Atlanta, GA: National Center for Chronic Disease Prevention and Health Promotion, Centers for Disease Control and Prevention.

Vazire, S., (2010). Who Knows What About a Person? The Self-Other Knowledge Asymmetry (SOKA) Model. *Journal of Personality and Social Psychology, 98,* 281-300.

Ware, J. E., Sherbourne, C. D. (1992). The MOS 36-Item Short-Form Health Survey (SF-36): I. Conceptual Framework and Item Selection. *Medical Care, 30,* 473-483.

Walton, K. E., & Roberts, B. W. (2004). On the relationship between substance use and personality traits: Abstainers are not maladjusted. *Journal of Research in Personality*, *38*, 515–535.

Weiss, A., Gale, C. R., Batty, G. D., &Deary, I. J. (2009). Emotionally Stable, Intelligent Men Live Longer: The Vietnam Experience Study Cohort. *Psychosomatic Medicine*, *71*, 385-394.

Williams, R. B. (2003). Invited Commentary: Socioeconomic Status, Hostility, and Health Behaviors–Does It Matter Which Comes First? *American Journal of Epidemiology*, *158*, 743.

APPENDIX A: HASCI RAW CORRELATIONS

A table containing raw correlations, means, and standard deviations of the variables derived from the HASCI KN data set that were used in this study can be found in the file named **hasci_correlations.pdf**.

APPENDIX B: GSOEP RAW CORRELATIONS

A table containing raw correlations, means, and standard deviations of the variables derived from the GSOEP data set that were used in this study can be found in the file named **gsoep_correlations.pdf**.

APPENDIX C: HRS RAW CORRELATIONS

A table containing raw correlations, means, and standard deviations between the variables derived from the HRS data set that were used in this study can be found in the file named **hrs_correlations.pdf**.