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Internet Use and Mental Health/Well-Being in Old Age: Exploring the Roles of Social Integration and Social Support

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INTERNET USE AND MENTAL HEALTH/WELL-BEING IN OLD AGE:
EXPLORING THE ROLES OF SOCIAL INTEGRATION AND SOCIAL SUPPORT

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ABSTRACT

The escalating pressures put on the US healthcare system, due in part to the growing needs of the expanding older adult population, has motivated research dedicated to more fully understanding the mental health and mental well-being needs of this population and ways to address these needs and alleviate the pressure on the healthcare system. An increasing area of interest is in examining the role information and communication technologies (ICTs), such as Internet-connected computers and smartphones, in the health of older adults. Research has shown that ICTs can successfully be used to help treat, manage, and cope with mental health/well-being issues, but previous literature also finds that ICTs can contribute to mental health/well-being outcomes more directly.

While studies have shown that ICTs may benefit older adults with regards to mental health/well-being, less is known through what mechanisms this relationship is enacted. This study uses data from the Health and Retirement Study to compare Internet-using older adults (aged 65+) with non-users on depression, life satisfaction, loneliness, personal growth, and purpose in life. Specific attention is given to examining the potential mediating roles of social integration (i.e., quantity of social ties) and social support (i.e., quality of social ties), as a Durkheimian perspective of Internet use argues that Internet use can be both beneficial and detrimental to an individual's social life, and changes in social life through Internet use can in turn affect mental health/well-being. Results of cross-sectional and longitudinal analyses finds Internet users, compared to non-users, typically enjoy more favorable mental health/well-being outcomes. Measures of social integration and social support are found to mediate the relationship between Internet use and mental health/well-being, but only partially. Additional analyses find that demographic characteristics, such as income and functional limitations, moderate the relationship between Internet use and mental health/well-being in older adults. The findings suggest that ICT interventions that incorporate elements that help older adults maintain social contacts and develop new ones may lessen mental health/well-being issues and the burdens associated with them.

Keywords: ICTs, mental health, aging, mental well-being, Internet, gerontology

DEDICATION

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LIST OF ABBREVIATIONS

CES-D	Center for Epidemiological Studies Depression Scale
HRS	Health and Retirement Study
ICC	intraclass correlation coefficient
ICTs	information and communication technologies
OLS	ordinary least squares
AGE75	age of respondent centered at 75
$AGE75^2$	age of respondent centered at 75, squared
$AGE75^3$	age of respondent centered at 75, cubed
INTERNET	Internet use
SEX	respondent sex
EDUCATION	years of education
RACE	respondent race
INCOME	income level
EMPLOY	employment status
HEALTH	self-rated health
FUNCTION	functional limitations
SOCCOMP	composition of social network
CLOSESPOUSE	close relationships with spouse/partner
CLOSECHILD	close relationships with children
CLOSEFAM	close relationships with other family members

CLOSEFRIEND	close relationships with friends
CONTCHILD	contact with children
CONTFAM	contact with other family members
CONTFRIEND	contact with friends
SUPSPOUSE	social support from spouse/partner
SUPCHILD	social support from children
SUPFAM	social support from family
SUPFRIEND	social support from friends

CHAPTER ONE

INTRODUCTION

With projections estimating the population of US older adults (aged 65+) more than doubling between 2010-2050 from 40 million to over 88 million, researchers anticipate the growing proportion of older adults will present challenges to health and healthcare both on the individual as well as the societal level (Administration on Aging 2012; Federal Interagency Forum on Aging-Related Statistics 2012; Vincent and Velkoff 2010). Particular interest has been placed on the mental health and the mental well-being of older adults; the proportion of older adults suffering from a mental health issue is currently 1 in 4 (National Council on Aging 2012) and, because of its relation to other health outcomes as well as the costs associated with treatment, the mental health and well-being issues of older adults are anticipated to significantly increase the economic pressures placed on the US healthcare system (Karlin and Fuller 2007; Karlin and Humphreys 2007; Knight and Sayegh 2011). It has thus become a primary focus of theoretical and applied social scientists to investigate what factors contribute to mental health and mental well-being in old age and what may mediate these factors; a clearer understanding of mental health/well-being in older adults may provide insight that can lead to the development of programs and interventions that can alleviate these issues and decrease the financial strains placed on the healthcare system.

A growing field of inquiry for researchers is in examining the relationship between information and communication technologies (ICTs), such as Internet-connected computers and smartphones, and mental health/well-being in old age. While a wealth of literature finds that ICT-based programs and applications can be used to help treat, manage, and cope with mental health issues (for example, see Perle and Nierenberg 2013), studies also find that ICT use itself can affect mental health/well-being; some studies find that ICT use can benefit individuals with regard to objective mental health outcomes like depression as well as more subjective mental well-being outcomes like loneliness (Cotten et al. 2012; Shaw and Gant 2002; Valkenburg and Peter 2007), while others find that ICT use can contribute to negative outcomes (Huang 2010; Lam and Peng 2010; Moody 2004; Prezza, Pacilli, and Dinelli 2004; Thomée et al. 2007; Thomée, Härenstam, and Hagberg 2011). A majority of the studies that find a detrimental relationship between ICT use and mental health/well-being present results that are not specific to the older adult population. Restricting the frame to older adults, most studies find that ICT use benefits the user (Chen and Persson 2002; Choi, Kong, and Jung 2012; Cotten et al. 2012, forthcoming; Ford and Ford 2009; Sum et al. 2008).

From a sociological perspective, it is not unusual that results investigating ICT use and mental health/well-being are inconsistent: while ICTs provide individuals with technological tools to develop new social relationships and enhance/reinforce established relationships, ICTs can also provide a means for some individuals to sever real-world social ties and retreat into a virtual world (DiMaggio et al. 2001). These positive or negative changes in social life, influenced at least partially by ICT use, can have drastic impacts on mental health/well-being, as numerous studies point to the effects of social relationships on mental status (for example, see Seeman 1996).

Applying this perspective, it can be argued that, in older adults, ICT use can have either a positive or negative effect on mental status based on how ICT use affects aspects of social life. From this emerges a query: what roles do aspects of social life, specifically social integration and social support, play in the relationship between ICT use and mental health/well-being in older adults? To address this research question, this study uses a combination of cross-sectional and longitudinal analyses of a representative sample of US older adults to determine if a relationship exists between ICT use and mental health/well-being and to determine if social integration and social support act as mediators in this relationship. Specifically, this study uses data taken from five waves (2004-2012) of the Health and Retirement Study (HRS) conducted at the University of Michigan's Institute for Social Research to determine if a relationship exists between ICT use (operationalized by Internet use) and various conceptualizations of mental health (depression) and mental well-being(life satisfaction, loneliness, personal growth, and purpose in life) and to determine if social integration (measured as composition of social network, number of close social relationships, and contact with social network) and social support mediate this relationship in a significant way. In addition to examining the potential mediating effects of social integration and social support, demographic characteristics are examined as potential moderators in the relationship between ICT use and mental health/well-being.

This investigation makes numerous significant contributions to the social science literature on ICT use and aging. First, while there has been growth in the number of studies focused on investigating ICT use and mental health/well-being in older adults, Ford and Ford (2009) argue that most of these studies utilize data with small sample sizes; use of the HRS dataset allows for a detailed investigation with a large sample that, in turn, allows for an analysis with increased statistical power. Second, while previous studies have explored the possibility of social integration and support as mediators in the relationship between ICT use and mental health/well-being (for example, see LaRose, Eastin, and Gregg 2001), few have examined this relationship specifically in older adults and thus results may not be applicable to the general older adult population. In addition, studies examining the relationships of Internet use and mental health/well-being typically conceptualize mental status as number of depressive symptoms and/or feelings of loneliness (Choi et al. 2012) and feature cross-sectional analysis (for example, see Chen and Persson 2002). Use of the HRS dataset in this investigation allows for both cross-sectional and longitudinal procedures that can explore various conceptualizations of mental health/well-being, including oft-used measures of depression and loneliness as well as life satisfaction, personal growth, and purpose in life. Finally, because of the growing concern on national spending for mental health services for older adults, the results of this study have the potential for significant application; by determining what roles Internet use, social integration, and social support have in determining mental health/well-being in the US aging population, researchers and policymakers may develop Internet-based interventions and strategies that can promote the mental status of older adults, thus decreasing the overall financial burdens placed on the US healthcare system.

CHAPTER TWO

LITERATURE REVIEW

Mental status and aging have become a primary concern in the health and social sciences. The use of medical care services generally increases with age (National Institute on Aging 2011), and with the rapid expansion of the older adult population (Vincent and Velkoff 2010) there is an expectation that pressure will be placed on overall healthcare spending in the US. This is especially true regarding mental health services, as the National Council on Aging (2012) estimates that 1 in every 4 older adults experiences a mental health issue (e.g., depression, anxiety, dementia) and the number of older adults suffering from a mental health disorder will double to 15 million by 2030. Mental health issues have also been shown to be significantly linked to morbidity and mortality, leading to speculation that as mental health problems increase, other health issues will arise; thus it is expected that the mental status of the aging population will significantly contribute to use of mental health and other health services, increasing the financial strains placed on the US healthcare system (Karlin and Fuller 2007; Karlin and Humphreys 2007; Knight and Sayegh 2011).

In response to this growing concern, applied social scientists have explored the specific mental health and well-being challenges of the older adult population in the hopes of better understanding the older adult experience as well as identifying ways to possibly decrease or alleviate mental health/well-being issues associated with aging, which could, in turn, decrease the pressures placed on the US healthcare system. This chapter begins with an outline of some of the ways mental health and mental well-being are conceptualized in the social science literature and continues by summarizing previous findings investigating the relationship between ICT use and mental health and mental well-being, both in the general population and specifically in the older adult population. The chapter concludes with a general summary of the theoretical basis for this study as well as a list of hypotheses used to guide the investigation.

Mental Health/Well-Being in Old Age

Due in part to the prevalence of cognitive problems in old age, late life is often characterized as a period of mental decline by the general public (Nelson 2007). While perceptions of old age as a negative period in the life course are often based on ageist stereotypes, research has shown that older adults fear the mental declines that are often associated with the aging process (Connell, Roberts, and McLaughlin 2007). Research has shown that these fears are also not completely unfounded, as numerous studies have found evidence to suggest that mental health, as well as subjective mental well-being, decline later in life (for example, see Mroczek and Spiro 2005; Ryff 1995; Ryff and Singer 2008; Yang 2007). For the purposes of this investigation, the term “mental health” will be used to describe objective measures of mental and cognitive status (i.e., conceptualizations that can be diagnosed by a healthcare professional) whereas “mental well-being” will be used to refer to more subjective measures (i.e., conceptualizations that are based more on the personal experiences, feelings, and opinions of the individual).

Ferraro and Wilkinson (2013) make the claim that, within the social sciences, depression and depressive symptomatology are the most widely used outcomes in the operationalization of mental health in aging populations. This is due in part to the prevalence of depression among older adults, as the Centers for Disease Control and Prevention (CDC) reports that as much as 5% of the older adult population may be living with depression, and this number increases to 11.5% for those in a hospital and 13.5% for those that require home healthcare (Centers for Disease Control and Prevention Healthy Aging Program 2012). A cursory review of the literature finds a myriad of studies dedicated to the investigation of depression later in life. Typically measured using a version of the Center for Epidemiological Studies Depression Scale (CES-D), studies of depression through the life course have found evidence of a U-shaped relationship between depressive symptoms and age; report of depressive symptoms tends to be highest in early adulthood and in old age and tends to be lowest in midlife (Clarke and Wheaton 2005; Kessler et al. 1992; Miech and Shanahan 2000; Mirowsky 1996; Mirowsky and Ross 1992; Ross and Mirowsky 2008; Schieman, Van Gundy, and Taylor 2001).

When restricting analyses to older adults only, depressive symptoms increase with age (Yang 2007). While depression is seen to increase later in life, research also shows that when accounting for *changes* in old age, such as physical and cognitive decline, age is no longer a significant predictor (Blazer 2003). In this way, age itself is not necessarily affecting depression; instead physical, cognitive, and social changes that typically occur late in the life course contribute more to increased depressive symptomatology.

Some theoretical explanations for this curve focus on the importance of social roles and relationships in mental health (Clarke et al. 2011). In adulthood, depression decreases over time with status/role gains (e.g., marriage, career) and increases later in life with the loss of these statuses/roles (e.g., widowhood, retirement). In this way social structures and conditions can significantly predict depressive symptomatology (Clarke et al. 2011). Other factors shown in previous research to have a significant relationship with depressive symptoms through the life course include experiencing transitional life events, education, stress, social support and coping resources, overall health, feelings of shame, and feelings of control (Schieman et al. 2002; Vink et al. 2009; Yang 2007), among others.

While depressive symptomatology remains a focus of mental health research in older adults, there is a growing body of literature investigating other facets of more subjective measures of mental well-being, including life satisfaction, loneliness, personal growth, and purpose in life. A global judgment of an individual's life (Diener 2000), life satisfaction is dependent upon individual standards based on personal circumstances and experiences and is thus often viewed as a central aspect of subjective well-being (Diener et al. 1985). In psychology, a prevailing theory proposed by Brickman and Campbell (1971) argued that in adulthood and old age life satisfaction remains fairly consistent. Described as the *hedonic treadmill*, the argument centered on the notion that "one's emotion system adjusts to one's current life circumstances and that all reactions are relative to one's prior experience" (Diener, Lucas, and Scollon 2006: 305), and thus positive or negative life events would only temporarily change life satisfaction levels before returning to a neutral position. While there is some literature to support this (for example, see Hsu 2010), other recent empirical findings have found evidence to refute this argument (for example, see Fujita and Diener 2005), supporting the notion that life satisfaction can change over time.

Regarding older adults, research has found that life satisfaction peaks around retirement age and then declines (Meléndez, Tomás, Oliver, and Navarro 2009; Mroczek and Spiro 2005) and that individuals are at significant risk of declining life satisfaction towards end-of-life (Gerstorf et al. 2008). Factors shown to affect life satisfaction include mood (Schwarz and Clore, 1983), personality (Diener and Lucas 1999), cultural norms/roles (Suh et al. 1998), happiness (Peterson, Park, and Seligman 2005), social engagement (Jang et al. 2004), and quality of social networks and social exchanges (Berg et al. 2006; Darbonne, Uchino, and Ong 2012), among others.

Loneliness is conceptualized as the difference in an individual's desired social relationships and perceived social relationships (Perlman and Peplau 1981). This is conceptually different from social isolation, an objective measure of a lack of contact with others; loneliness, while related, is the subjective negative experience of social isolation (Wenger et al. 1996). Quality of personal relationships is a strong predictor of health (Dykstra 2007) and loneliness has been significantly linked to physical factors such as blood pressure and sleep quality as well as mental factors like depression and cognition (Luanaigh and Lawlor 2008). Because of its predicting power for a variety of health outcomes, loneliness has become a central focus of research on older adults, particularly due to the general image that older adults are at a severe risk for increased loneliness (Abramson and Silverstein 2006; Tornstam 2007; Victor et al. 2002); however, the legitimacy of this stereotype has come into question (for review, see Dykstra 2009). Predictors for loneliness include objective measures such as widowhood, education, income, health and disability status, and living arrangements (Russell 2009; Savikko et al. 2005; Victor et al. 2005) as well as subjective measures such as a lack of friends and satisfaction with social contacts (Routasalo et al. 2006; Savikko et al. 2005).

Personal growth and purpose in life have previously been conceptualized as specific dimensions of psychological well-being (Ryff 1995, 1989; Ryff and Keyes 1995). Other dimensions of psychological well-being, as defined by Ryff (1995; 1989) include autonomy, environmental mastery, positive relations to others, and self-acceptance; however, personal growth and purpose in life are of particular interest in aging research, as studies find that older cohorts typically report lower scores for these measures compared to young and middle-aged cohorts (Ryff 1995; Ryff and Singer 2008). Personal growth captures subjective feelings of personal development, expansion, and improvement, while purpose in life measures subjective feelings of life direction, meaning, and goals/objectives (Ryff 1995). Both dimensions have shown to be significantly linked to aspects of biological health in older adults, like neuroendocrine regulation, such that those with higher scores of personal growth and purpose in life experienced better health outcomes (Ryff and Singer 2008).

While mental health and subjective mental well-being can be conceptualized in a number of ways, there is consistency across the literature suggesting that older adults are at risk for lower levels of mental health/well-being and that these lower levels contribute to negative health outcomes. Studies investigating predictors of mental health/well-being and factors that may promote mental health/well-being in old age have thus become prevalent across a variety of disciplines. An emerging field of inquiry focuses on the possible effects ICT use may have on mental health and subjective well-being.

Mental Health/Well-Being Consequences of ICT Use

ICTs include computer-based or computer-assisted devices or applications used for the purposes of the dissemination of information or for communication with others. In research, the term ICT is often used to describe devices or applications connected to the Internet, such as Internet-connected computers or smartphones. ICT use in the US has steadily increased over the past decade with the introduction of high-speed Internet connections and new Internet-connected devices. The Pew Internet and American Life Project, which routinely conducts surveys to gauge trends in ICT ownership and use in the US, finds that the percentage of US adults who report using the Internet has climbed from approximately 50% in 2000 to 87% in 2014 (Pew Internet and American Life Project 2014), and this increase in usage has coincided with increases in broadband connectivity (Pew Internet and American Life Project 2012) and increases in ownership of devices like laptops, tablet computers, and smartphones (Pew Internet and American Life Project 2013). Because of the growing propensity for US adults to own and use ICTs, social scientists have become interested in exploring how using these technologies can positively or negatively affect the user.

An emerging literature focuses on how ICTs can be used to help treat, manage, or cope with physical and mental health issues. As an example, with the growing popularity of smartphones there has been growing interest in the use of smartphone applications in the management of diabetes; research has found that use of diabetes-monitoring smartphone applications improves self-monitoring of blood glucose levels and allows health care providers to easily and accurately review a patient's condition and provide feedback (for a review, see Tran, Tran, and White 2012). ICTs have also been shown to successfully assist in the management of asthma, monitor adherence to vitamin regimens, promote and monitor weight loss/physical activity, and assist in smoking cessation (for review, see Cole-Lewis and Kershaw 2010). For mental health, particular focus has been placed on managing depressive symptoms through the use of therapies delivered online, and evidence suggests that online therapies have been successful in treating and managing depressive symptoms (for review, see Kaltenthaler et al. 2008).

Yet while ICTs have been found to be useful tools in treating and managing specific health conditions, researchers have also been interested in determining if ICTs have any direct effect on health as well, and in this regard findings have been somewhat inconsistent; evidence exists for both a beneficial and detrimental effect associated with ICT use. In a widely-cited study where college students participated in anonymous online chat sessions, Shaw and Gant (2002) found that depression and loneliness decreased among participants while self-esteem levels increased. However, another widely-cited early study conducted by Kraut et al. (1998) found opposing results; in a sample of Pittsburgh-area families, use of the Internet was associated with increased depression and loneliness. It should be noted, however, that a 3-year follow-up of this sample found that the negative effects of Internet use dissipated over time, and a separate study of Pittsburgh households that had purchased a new computer/television found Internet use was positively associated with trust and positive affect (Kraut et al. 2002). Valkenburg and Peter (2007) also found a positive impact of ICT use, finding that Internet-based communication among adolescents could positively impact life satisfaction. Regarding more negative findings, Lam and Peng (2010) found that in young Chinese adolescents, mental health issues such as depression could develop in those who excessively or pathologically used the Internet. Prezza et al. (2004) found that Internet use was positively associated with loneliness in Roman adolescents, and Moody (2004) also found an association between Internet use and loneliness, specifically emotional loneliness. The work of Thomée and colleagues (Thomée et al. 2007; Thomée, Härenstam, and Hagberg 2011) examined the use of computers and mobile phones in young adults and found that increased ICT use was associated with increased depression, stress, and sleep disturbances. Finally, a meta-analysis conducted by Huang (2010) found a small but significant correlation between high Internet use and reduced well-being.

Older Adults and ICT Use

Prior to a discussion on the previous studies specifically examining the mental health/well-being effects of ICT use in older adults, it is important to highlight the differences in ICT use between older adults and the general population, as the proportion of older adults online, compared to other cohorts, is much lower (Pew Internet and American Life Project 2014; Zickuhr and Madden 2012). The next section outlines the rate of ICT use in older adults as well as summarizes literature that attempts to explain this gap.

Technology Adoption and the Digital Divide

Statistics reported by the Pew Internet and American Life Project find that while use of ICTs in older populations is increasing, the proportion of Internet-using older adults is still much lower than other age cohorts (Zickuhr and Madden 2012). In 2001, only 15 %

of Americans aged 65+ reported going online (Fox et al. 2001) but that number has increased to 53% by 2012 (Zickuhr and Madden 2012) and to 59% by 2013 (Pew Research Internet Project 2013). This percentage is still lower than other age groups: Pew reports that in 2012 97% of adults 18-29 reported being online, compared with 91% of those 30-49 and 77% of those 50-64 (Zickuhr and Madden 2012). Restricting the scope to those aged 75+, only 34% report using the Internet. There is a noticeable gap in connectivity between age groups, prompting researchers to examine why older adults do not use ICTs to the same degree as other groups.

Theories of technology adoption partly explain why Internet use is more prominent in some groups compared to others. The Technology Acceptance Model (TAM), a model often used in information systems research, proposes that technology use is motivated by perceived usefulness and perceived ease of use; that is, a technological system is more likely to be accepted and adopted if it is perceived by the user that it will enhance role performance and that the overall effort needed to learn/master the system is relatively low (Davis 1989). While often applied to technologies found in the workplace, the TAM model has also been adapted for consumer products: as an example, Bruner and Kumar (2005) applied the TAM model to consumers' acceptance of mobile Internet devices and found that perceived usefulness, as well as the overall enjoyment of the devices, contributed to device adoption. While several theorists have highlighted limitations to the TAM model (such as use of self-reported data in TAM studies; for a review of other limitations, see Chuttur 2009; Legris, Ingham, and Collerette 2003) it is still one of the most widely used in information systems research. Renaud and van Biljon (2008) present an expansion of the TAM model for older adult technology acceptance that also incorporates aspects of similar models, like the Unified Theory of Acceptance and Use of Technology (UTAUT) and Mobile Phone Technology Acceptance Model (MOPTAM). Titled the Senior Technology Acceptance and Adoption Model (STAM), Renaud and van Biljon argue that perceived usefulness and perceived ease of use alone cannot account for actual technology use, as use can also be highly motivated by user context (e.g., social and individual characteristics), intentions to use, experimentation and exploration, confirmed usefulness, and perceived ease of learning.

Focusing strictly on older adults, studies show that technology adoption, or a lack thereof, can at least be partly attributed to a lack of perceived usefulness and difficulties with learning/mastering the technology. Regarding usefulness, many older adults believe that newer technologies have little relevance to them (Selwyn et al. 2003) and thus experience “motivational indifference” towards ICTs (Peacock and Künemund 2007). Regarding ease of use, barriers preventing older adults from successfully adopting technologies include perceptions of being too old to learn, general embarrassment over a lack of initial ability to use, physical declines that affect visual ability and hand dexterity, and cognitive declines that affect the learning process and memory (Boulton-Lewis 1997; Boulton-Lewis, Buys, and Lovie-Kitchin 2006; Boulton-Lewis et al. 2007; Broady, Chan, and Caputi 2010; Gatto and Tak 2008; Hanson 2010; Purdie and Boulton-Lewis 2003; Renaud and Ramsey 2007; Timmerman 1998).

Yet while TAM and STAM can explain part of the reason why older adults use technologies less than their younger counterparts, ICT researchers argue that inequalities in access to these technologies, as well as inequalities in access to the necessary education needed to master these technologies, may also contribute to low levels of usage. Inequalities related to Internet-based technologies are often referred to as the "digital divide." While a conceptualization of the digital divide can incorporate aspects of TAM, such as perceived usefulness and ease of use, it has often been used to describe differences between the "haves and have nots:" those with or without a computer, those with or without access to the Internet, and those who report being ICT users or non-users (for a review, see Hargittai 2002). This comparison of "haves and have nots" is often referred to as the "first-level digital divide," whereas barriers to use beyond ownership and access (e.g. ability to learn, skill level, attitudes towards technology, etc.) are referred to as the "second-level digital divide" (Hargittai 2002; Millward 2003). While Internet use among older adults has drastically increased over the past decade, Pew reports that only 39% of adults aged 65+ have broadband in the home (Zickuhr and Madden 2012). Thus while decreased use of the Internet can be partially attributed to individual attributes such as perceived benefits and ease of learning (aspects of the second-level digital divide), more macro forces like Internet access/affordability can also have a significant impact on technology adoption (aspects of the first-level digital divide). As can be seen, despite the prevalence of ICTs in everyday life there are numerous factors that come into play that can prevent older adults from successfully utilizing the technology.

Mental Health/Well-Being Effects of ICT Use in Older Adults

While the previously outlined literature provides evidence in support for arguments on both the beneficial and detrimental effects of ICT use on mental health/well-being, when restricting analyses to older age groups the research consistently reveals a more positive relationship between ICT use and mental status such that users experience better outcomes. Early intervention studies conducted in the late 1990's and early 2000's by White and colleagues (1999; 2002) were among the first to highlight a potential positive relationship between ICT use and mental health/well-being for older populations. In the first, White et al. (1999) conducted a pilot investigation in a retirement community to investigate how ICTs could affect psychosocial well-being. Results found that the experimental group that received training in computer use experienced reduced feelings of loneliness, compared to a control group that received no training. In a follow-up study, White et al. (2002) found that study participants who received ICT training trended towards decreased loneliness and depression when compared to a control group, although it should be noted that the differences between the experimental and control groups were not statistically significant.

Other studies have found evidence to suggest a positive association between ICT use and mental health/well-being in old age over a diverse set of outcomes. Investigating ICT use both in young adults and older adults, Chen and Persson (2002) found that older Internet users, compared to non-users, scored higher in psychological well-being, particularly personal growth and purpose in life. Examining Internet use in Australia, Sum et al. (2008) found that greater Internet use was associated with lower levels of loneliness. Similar results were found by Choi et al. (2012): conducting a meta-analysis of ICT-based intervention studies in older adults, the authors found that Internet use was associated with decreased loneliness in the included studies. Decreased loneliness was also found in a recent study by Cotten, Anderson, and McCullough (2013): investigating Internet use in older adults residing in assisted and independent living communities, the authors found that increased frequency of going online was associated with decreases in loneliness, but interestingly was not significantly associated with perceived social isolation. Examining older adults in the rural Midwest of the US, Stark-Wroblewski, Edelbaum, and Ryan (2007) found that older adults who used email were less likely to report health limitations and more likely to have increased feelings of independence. Ford and Ford (2009), using data from the Health and Retirement Study (HRS), found an inverse relationship between Internet use and depression scores in older adults, and these results were consistent even when attempting varying analytic techniques such as linear probability models and propensity score methods; Cotten et al. (2012) also examined Internet use and depression in the HRS and found, through the use of regression and propensity score methods, that Internet use was associated with a 20-28% decrease in depression categorization. A follow-up by Cotten et al. (forthcoming) using longitudinal analysis with HRS data found similar results, as Internet use was associated with a 33% decreased probability of depressed categorization. Investigating the effects of ICT use on cognitive decline, Slegers, van Boxtel, and Jolles (2012) found that older adults who reported using computers and the Internet had better attention and memory scores, and the older adults interviewed for the study also felt that computer use positively affected autonomy and cognition. Finally, a qualitative study of older Chinese conducted by Xie (2007) found that respondents who used the Internet "felt younger" and compared themselves positively with younger cohorts.

Not all studies investigating ICT use in older populations find a positive effect on mental status, as some find no significant relationship between Internet use and mental health/well-being. As an example, while the above study by Slegers et al. (2012) found a protective effect of ICT use with regards to cognition, an earlier study (2008) found no significant effect, positive or negative, of ICT use on functioning, well-being, or mood. Examining older adults in Spain, Gracia and Herrero (2009) found that while Internet use was associated with better measures of self-rated health, these effects were explained away once socioeconomic status was included in the models. Dickinson and Gregor (2006) argue that while numerous studies support a positive impact of ICT use in old age, the results of these studies should be approached with caution as they have significant limitations, including: inability to account for ICT training support and interaction with training personnel, inability to determine true direction of causation, and inappropriate generalization of results to the general older adult population. Dickinson and Gregor thus make the claim that, at the time of their writing, no evidence had been found to support the argument that Internet use directly affects mental health/well-being in a positive way. Despite these studies that find no effect of ICT use on mental status, and despite the arguments made by Dickinson and Gregor, the overwhelming majority of studies focused on older adults find a positive association of ICT use on outcomes such as depression and loneliness. Even so, it is still unclear through what mechanisms ICTs affect the mental status of older adults.

Social Integration and Social Support as Mediators

While older adults are less likely to utilize ICTs compared to younger cohorts, the proportion of users is growing and the empirical literature thus far supports the argument that older adults benefit from their use. The consistency found in the aging research is in stark contrast to the literature focusing on other groups, begging the question: why is there a consistent positive finding for older adults but not for other populations? A possibility is that there are mediators at play in the relationship between ICT use and mental health/well-being, and that these mediators operate differently in older adults compared to other groups.

Mediating variables, briefly, help to explain the effects of an independent variable on a dependent variable. While it is possible that a direct relationship may exist between two variables, oftentimes there are other factors at play that can affect this relationship. In mediation, an independent variable is not directly influencing a dependent measure; rather, the independent variable is having a significant effect on a third measure (a mediating variable). Changes in the mediating variable, brought on by the independent variable, are what motivate change in the dependent variable. The process of mediation, as well as basic statistical considerations regarding testing for mediation, is outlined by Baron and Kenny (1986).

The theoretical argument at the center of this investigation proposes that, in the relationship between ICT use and mental health/well-being, aspects of social life act as mediators. More specifically, it is argued that use of ICTs affects individuals' level of social integration and social support by providing the technological means to expand and reinforce social bonds, and these ICT-influenced changes in social life affect overall mental status. Previous studies have examined the potential for factors of social life influencing the relationship between ICT use and mental status (Bessière et al. 2008; Ellison, Steinfeld, and Lampe 2007; LaRose et al. 2001; Valkenburg and Peter 2007), although it should be noted that a majority of studies examining social integration and support as mediators have been cross-sectional investigations and have focused on students and/or adolescents (the previously cited Bessière et al. 2008 article being an exception). The next sections detail the theoretical arguments explaining how social integration and social support may act as mediators in the relationship between ICT use and mental health/well-being.

Social Integration

Social integration, as defined by Bissette, Cohen, and Seeman (2000: 54), refers to "the extent to which an individual participates in a broad range of social relationships." It is a structural aspect of human relationships, a measure of the *quantity* of social ties and can be operationalized as the number of ties in a social network. Social integration measures can also incorporate other network properties, such as frequency of contact and network density (Thoits 2011).

Theories explaining the purpose and influence of social integration date back to Durkheim (1893; 1897). In *The Division of Labor in Society*, Durkheim (1893) argues that social integration is a consequence of modernity and a society's increased sense of individualism. Durkheim contends that, in primitive societies, the natural order of things is defined by a collective conscious wherein individual members placed faith and reliance on the beliefs and actions of the group (a "totality of a group's beliefs and sentiments; see Ritzer and Goodman 2004: 76); this was the social structure of early hunter-gatherer societies However, as societies moved towards modernity a division of labor emerged in which the collective conscious of the group was replaced by individualism. Group members specialized in certain tasks, earning a distinct role in the group and promoting overall productivity of the group. A new type of reliance emerges from this increased individualism, because although group members have less stock in the collective conscious they no longer have the skills to carry out all responsibilities for daily living and thus must rely on other group members for survival. In this way it becomes necessary for group members to continue to interact with one another and to integrate themselves into the evolving social structure, as failure to do so may have negative consequences on the individual and the society as a whole. According to Durkheim, social integration was a necessary consequence of modernity and increased economic productivity.

Durkheim continues his discussion on social integration in *Suicide* (1897), theoretically explaining how a macro-level concept as social integration can significantly affect micro, or individual, outcomes. In *Suicide,* the individual outcome Durkheim examined was the individualistic and personal act of taking one's own life. Examining the suicide rates of a different groups, Durkheim finds patterns suggesting that the social structures of different groups could in fact motivate suicide, making what was originally viewed as a very personal act appear as if having a social causation. Durkheim contends that having too little or too much social integration could motivate an individual to commit suicide. He argues that those with too little social integration would lack a feeling of purpose and support and would not feel like a part of society; in this case, the individual would commit *egoistic* suicide. In *Suicide* Durkheim found evidence to suggest that those who were unmarried (i.e., less integrated into a familial unit) and those participating in religions that emphasized individual rather than community faith had higher suicide rates; he also found that suicide rates would go down in areas where a sense of national community was strong, such as in countries at war. Those with too much integration, in contrast, would feel a nearly overwhelming devotion to society and would commit suicide for the betterment of the group as a whole; Durkheim called this *altruistic* suicide, and a common example of this type of suicide is found in examining the motivations of martyrs. Another example of *altruistic* suicide discussed by Ritzer and Goodman (2004: 89) focuses on the mass suicide of followers of Reverend Jim Jones in 1978; these followers, due to the high level of integration into Jones' fanatic religious group, willingly committed suicide in support for their leader. In both cases of *egoistic* and *altruistic* suicide, Durkheim contends that the extent of social relationships and integration into society's social structure affected a very individual act.

Durkheim's early work on social integration was a turning point for social scientists studying health outcomes, as it provided theoretical arguments exploring how macro concepts of social life could affect individual outcomes. Since the publication of Durkheim's works, other social scientists have expanded social integration theory and applied it to the study of individual health outcomes, examples of which include Faris (1934), Sieber (1974), Marks (1977), and more recently Thoits (1983, 2011). In the social integration literature, Faris' work is notable as it is one of the earliest to link factors of social life to mental health outcomes. Using hospital records of schizophrenic patients, Faris (1934) was able to theoretically link social integration and isolation with mental health, as he found that those suffering from schizophrenia also had a decreased number of social contacts. Sieber, also linking social life and mental health, argued that mental well-being could be influenced by the accumulation of social roles. While sociologists previous to Sieber argued that accumulation of social roles could be detrimental to well-being through role strain (for example, see Goode 1960), Sieber postulated that the positive effects of accumulating social roles would outweigh the negative effects, and thus having increased social integration and a diverse social environment would have a positive effect on well-being (1974). Positive effects outlined by Sieber included accumulation of role privileges, increased status security, better status and role performance, and increased self-esteem (1974). Marks (1977) also argued that the benefits of role accumulation and increased social integration would outweigh the potential stresses associated with enacting multiple roles simultaneously, as he argued that accumulation of roles could contribute significantly to resources such as wealth and prestige. Thoits (1983, 2011) contributes to this discussion, adding that role accumulation can also provide meaning in an individual’s life and a lack of social integration can contribute to a negative mental state.

Social Support

In contrast to social integration, social support refers to the *quality* of social ties (House 1987) and refers to the functional content or the functions performed by primary and secondary others for individuals (Thoits 2011). As originally outlined by House and Kahn (1985) and explained by Thoits (2011), social support generally arises in three forms: emotional, instrumental, and informational. Emotional support “refers to demonstrations of love and caring, esteem and value, encouragement, and sympathy” (Thoits 2011: 146). Instrumental support refers to the supplying of behavioral or material provisions to assist an individual in practical situations (e.g., offering to drive someone to the doctor if they lack other transportation) (Thoits 2011). In contrast to this, informational support refers not to behavioral or material assistance with issues but instead highlights “the provision of facts or advice that may help a person solve problems" (Thoits 2011: page 146). While conceptually different, social integration and social support are theoretically linked in that social support cannot be present without the existence of at least one social tie; in this way the functional component of social relationships, social support, is somewhat dependent on the structural component, social integration (Lin, Ye, and Ensel 1999). Despite this, House (1987: 139) argues that "social integration and social support have somewhat independent effects on health."

Lakey and Cohen (2000) outline three perspectives in which social scientists have applied the concept of social support to the discussion of health outcomes. The first, the stress and coping perspective, argues that social support acts as a buffer between stress and health outcomes and contributes to an individual's ability to cope with stressful life events. This perspective also argues that perceived social support can contribute to positive appraisals of stressful events; that is, the belief that social support is available can motivate an individual to believe that events are less stressful than initially interpreted. The second perspective, referred to as the social constructionist perspective, grows out of the social cognition and symbolic interactionist tradition and argues that perceived support, regardless of whether or not it actually exists, contributes to feelings of self-esteem and identity, and increased positive thoughts of the self are thought to contribute to better health outcomes. The final perspective, the relationship perspective, contends that qualities of relationships (i.e., companionship, intimacy, conflict) must be taken into account when investigating social support and health; in this perspective it is often postulated that these relationship qualities also affect factors such as self-esteem and identity (which in turn affect health), and thus "measures of support cannot be discriminated from closely associated concepts such as low conflict, companionship, intimacy, and social skill" (Lakey and Cohen 2000: 42).

Taken together, both social integration and social support have strong theoretical ties to health (for a review and explanation of mechanisms not discussed in this proposal, see Thoits 2011). In theory, increased positive integration and support contribute to better outcomes. From here, ICT researchers investigating the mental health/well-being of older adults must determine if ICTs positively or negatively affect these social constructs, as ICT-related changes in social integration and support could theoretically influence health.

It should be noted that while this investigation places emphasis on the potential positive aspects of social relationships, there is a body of literature that suggests that the negative aspects of social life may also affect health (for review, see Lincoln 2000; Rook1990). As outlined by Lincoln (2000), negative interactions between individuals can actually have adverse effects on mental health/well-being; examples of negative interactions include conflicts between family/friends, unwanted or unneeded interactions, social undermining, and relationships that cause general stress, to name but a few. These negative interactions are more closely related to social support rather than social integration, as the health consequences stem from the *quality* of the social ties rather than the *quantity*, although one can assume that as social integration increases, the likelihood that at least one relationship would prove detrimental would also increase. Having said this, this study focuses *only* on the potential positive aspects of social relationships. The reasoning is two-fold: (1) as detailed in the next section, the theoretical argument presented in this proposal suggests a positive influence of ICT use on social life and mental health/well-being, and (2) positive aspects of social interactions and negative aspects cannot be measured through the use of one construct, and examining negative interactions would thus greatly expand the scope of the analysis. For these reasons, the positive aspects of social life are solely examined.

Linking ICT Use, Social Integration and Support, and Mental Health/Well-Being

Applying sociological perspectives to ICT use, DiMaggio et al. (2001) argue that ICTs have the potential to enhance social life as well as hinder it. As a positive influence, DiMaggio et al. (2001) contend that the Internet provides users with a unique means of communication that can be used to access and reinforce established social relationships (e.g., friends and family) as well as develop new social relationships. In this way, use of ICTs can contribute to increased social integration and social support, as use may increase the number of social ties an individual has as well as potentially increase access to networks that can provide emotional, instrumental, and informational support. An example of empirical literature that supports this perspective can be found in a paper by Ellison, Steinfeld, and Lampe 2007, who found that use of the social networking site Facebook contributed to the creation and maintenance of various forms of social capital[*]. In contrast to this, DiMaggio et al. (2001) also argue that ICT use can have a negative effect on social life. Using the language of Durkheim, the authors contend that Internet use may lead to a state of *anomie* (i.e., lacking in norms) and motivate individuals to retreat from the real world into a virtual one. In this way ICT use may contribute to an

[*] Social capital refers to the expected benefits of social interaction. While not the focus of this study, it is related to social integration and social support in that social capital is dependent both on the existence (i.e., quantity) of social ties as well as the closeness (i.e., quality) of social ties.

erosion of social ties and social support as users spend more time online and sever relationships with family and friends, thus decreasing overall social integration and support. This was touched upon by Nie (2001) who, in a review of survey research on Internet use and sociability, argued that Internet use reduced in-person interactions and communication. These dueling perspectives, from a theoretical standpoint, are both possible and contingent upon how the technology is ultimately used.

Using the arguments posed by DiMaggio et al. (2001) it is thus possible to argue that ICT use may have both a beneficial and detrimental effect on mental health/well-being. If ICT use has a positive relationship with social integration and support then the ultimate effect on mental health/well-being would also be positive, as increased social integration and positive social support have been shown to have a positive influence on mental health/well-being. Conversely, if ICT use erodes social relationships, then it can be assumed that the negative influence on social integration and support would have a detrimental effect on mental health/well-being.

Studies have been conducted examining ICT use, social integration and support, and mental health/well-being (for example, see Ellison, Steinfeld, and Lampe 2007; LaRose, Eastin, and Gregg 2001; Valkenburg and Peter 2007) and have found that ICT tends to increase social integration and/or social support, which in turn has a beneficial effect on mental status. As an example, LaRose, Eastin, and Gregg (2001) found that Internet use allowed individuals to access positive social support through the use of email, and this access contributed to decreased levels of depression. These studies and others, however, are limited in that they tend to focus on younger populations and/or use cross-sectional methodologies. This project would make a significant contribution to the literature by conducting a longitudinal analysis to determine if there is a relationship between ICT use, social integration and support, and various constructs of mental health/well-being strictly in a sample of older adults. It is important to focus attention on this segment of the population due to the increased risk of declining mental status in old age.

To guide this investigation, a conceptual model and five general hypotheses are presented based on the previous empirical literature as well as the theoretical literature on social integration and support. It should be noted that these five hypotheses will be tested over five different operationalizations of mental health/well-being; for brevity, separate hypotheses are not written out for each outcome.

Hypothesis 1: For older adults, mental health/well-being will decrease over time.

This hypothesis is based on the empirical literature suggesting that measures like depression and loneliness increase in old age, while life satisfaction, personal growth, and purpose in life all decrease.

Hypothesis 2: For older adults, Internet-users will experience better mental health/well-being compared to non-users.

This, again, is based on previous investigations suggesting a beneficial effect of using ICTs in old age.

Hypothesis 3: For older adults, the trajectory for mental health/well-being decline will be more favorable for Internet users, compared to non-users.

The expected declines in mental health/well-being will be greater for older adults who do not use ICTs.

Hypothesis 4: For older adults, social integration will act as a partial mediator in the relationship between Internet use and mental health/well-being.

Hypothesis 5: For older adults, social support will act as a partial mediator in the relationship between Internet use and mental health/well-being.

These are based on the theoretical literature on social integration and support as well as on previous findings on other populations suggesting a role of social relationships in determining the effect of ICT use on mental status. Only partial mediation is hypothesized, however, as previous studies have found that when accounting for social interactions, ICT use still serves as a significant predictor of mental health/well-being (for example, see Shapira, Barak, and Gal 2007). This implies that while ICTs may affect mental health/well-being through changes in social integration and social support, there may also be a direct effect of ICT use on these outcomes.

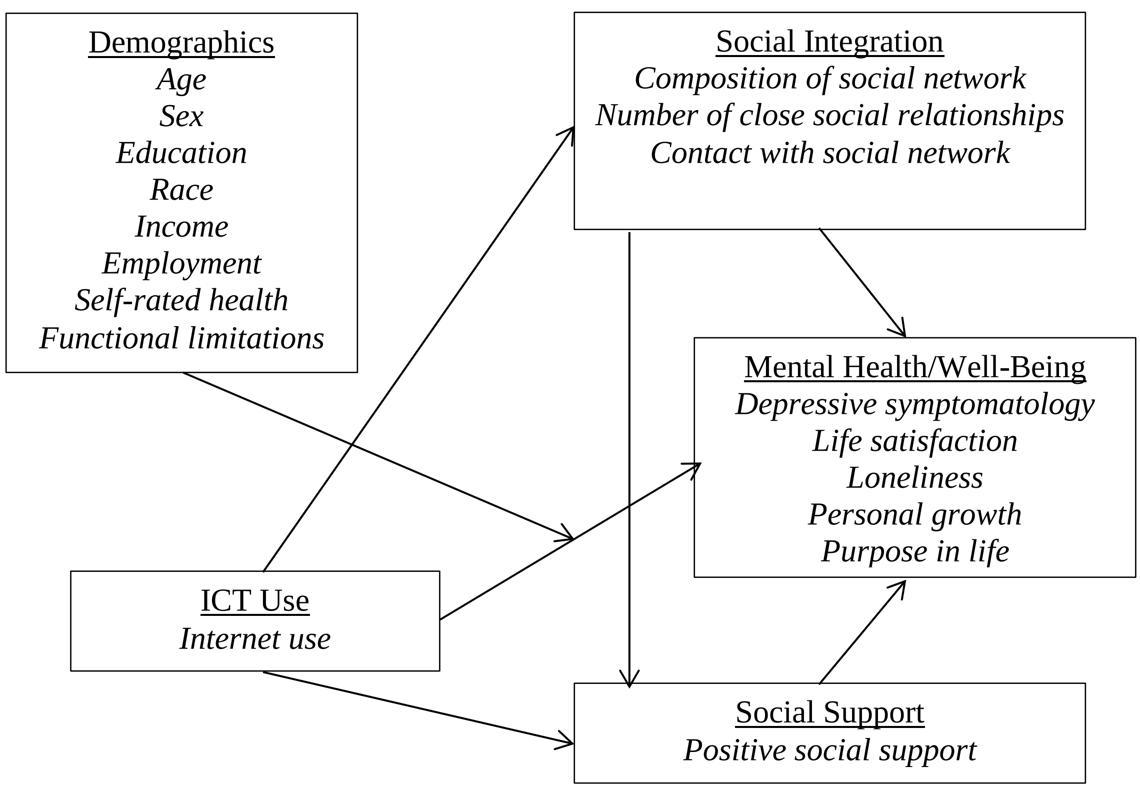

Figure 2.1: Conceptual Model

Interactions between ICT Use and Demographic Characteristics

While the primary focus of this investigation is in examining the roles social integration and social support play in the relationship between ICT use and mental health/well-being in older adults, a secondary objective is in examining the potential for moderation (i.e., interaction) effects with demographic moderators. In contrast to a mediation effect, which predicts that a variable will affect a mediator that will in turn affect an outcome, moderation effects predict that a variable will have a different effect on an outcome depending on the status of the moderator. As summarized by Baron and Kenney (1986: 1174), a moderator is a "…variable that affects the direction and/or strength of the relation between an independent or predictor variable and a dependent or criterion variable." An example of a moderation effect would be to examine the relationship of widowhood and depression. Loss of a spouse can potentially increase depression, however studies have shown that the increase in depression can be far greater for men than women (e.g., see Lee et al. 2001); in this example, sex moderates the effect of widowhood on depression levels.

It is possible that the effect of Internet use on mental health/well-being for older adults will be moderated by demographic characteristics. An example may be education levels, as it is reasonable to assume that those with higher education levels may be better equipped to utilize the Internet to its full potential in reducing negative health outcomes. For this investigation, moderators that are examined include age, sex, education, race, income, employment status, self-rated health, and functional limitations.

CHAPTER THREE

METHODS

The purpose of this study is to examine the relationship between ICT use and mental health/well-being in older adults and to determine what roles, if any, social integration and support play in this relationship. To accomplish this, data from the HRS are used to examine the relationships between Internet use, social integration and support, and a variety of mental health/well-being outcomes including depression symptoms, life satisfaction, loneliness, personal growth, and purpose in life.

Data

The HRS is a longitudinal study conducted at the University of Michigan's Institute for Social Research and supported by the National Institute on Aging (NIA). Started in 1992, the purpose of the study is to collect information on a nationally representative sample of US older adults, aged 50+, on topics pertaining to the unique challenges of this age group, including but not limited to: physical and mental health, insurance, finances, family and social support, and work and retirement (National Institute on Aging 2007). The core HRS dataset consists of 6 separate sub-samples. The first, and original, 1992 sample was generated from a screening of 69,337 households using a multi-staged, clustered probability frame; of these households, 59,918 were determined to be occupied households and all but 214 were successfully screened for eligibility (screening rate =

99.6%). The original 1992 sample consisted of individuals born 1931-1941, and of the 15,497 individuals who were deemed eligible for the study (including individuals identified from the household screening as well as their spouses/partners), interviews were completed for 12,652 (overall response rate = 81.6%) (Health and Retirement Study 2011).

The second sub-sample of the HRS comes from the Asset and Health Dynamics among the Oldest Old (AHEAD) study, which includes individuals born in 1923 or earlier. This sample was also identified through the same household procedure described above and by Medicare enrollment files. The AHEAD sample originally obtained 8,222 respondents (response rate = 80.4%) and was merged into the HRS in 1998 (Health and Retirement Study 2011). Two other sub-samples were merged into the HRS in 1998: the War Baby (WB) sample, consisting of individuals born 1942-1947 (baseline response rate = 72.5%), and the Children of the Depression Age (CODA) sample, consisting of individuals born 1924-1930 (baseline response rate = 70.0%). The two final sub-samples of the HRS were added in 2004 and 2010 and introduced a cohort of individuals born 1948-1953 (baseline response rate = 68.7%) (Health and Retirement Study 2011) and a cohort of individuals born 1954-1959 (baseline response rate currently unavailable as of this writing). Adding all sub-samples together, the HRS has collected data on over 20,000 participants since its start in 1992 (National Institute on Aging 2007).

Core data is collected every two years through a combination of face-to-face, telephone, and mail-in interviews, and “off-time” data has been collected through these methods as well as through online surveys. The “off-time” interviews typically use a random sample of the entire HRS dataset and examine a specific aspect of the aging process. Due to the over-sampling of minority respondents, and due to the fact that each sub-sample of the HRS is of unequal size, sample weights are calculated and available from the HRS to help approximate the age and racial/ethnic profile of older adults in the US (for details on how the weights are calculated, go to (http://hrsonline.isr.umich.edu/sitedocs/wghtdoc.pdf)).

Because the HRS consists of a large number of older adults in the US that are interviewed over time, this particular dataset allows researchers to examine such factors as ICT use, social integration/support, and mental health/well-being through longitudinal procedures. A limitation of many ICT studies is that the direction of causation can only be inferred due to the use of cross-sectional analyses; use of the HRS data can help solve this issue. Internet use was measured in the core data in 2002 and has been measured in every core survey since. For this investigation, surveys from 2004-2012 will be used (five waves total).

The HRS collects data on US adults aged 50+. However, because the focus of this study is on older adults, the analytic samples are restricted based on age. For each analysis (which will be detailed later in the chapter), the sample is restricted to individuals aged at least 65. In addition, cognitive functioning was used as an exclusion criterion in selecting the analytic sample. In the HRS respondents were asked a variety of questions used to measure cognitive ability. A summary variable was created in the HRS data that incorporates many of these measures, including immediate word recall, delayed word recall, "serial 7s" (a task that requires respondents to count by intervals of 7), backwards count from 20, object naming, President/Vice President identification, and naming of the date. This summary variable has a range of 0-35, wherein higher scores indicate higher cognitive functioning. For this study, respondents were excluded from the analysis if they scored more than 2 standard deviations below the mean. After calculating the mean and standard deviation this produced a cut-off score of 12, and so any HRS respondent who scored less than 12 on total cognition was excluded from analysis (a total of 488 were dropped due to this criterion). This was done to assure that results were not adversely affected by cognitive difficulties that could affect survey answers (e.g., if respondent's cognitive ability prevents them from understanding the questions asked).

Measurement

The primary outcomes of the investigation include variables that conceptualize aspects of mental health and subjective well-being. Number of depressive symptoms has been used extensively in aging and health research as a proxy for overall mental health and has been the focus of other ICT studies (for example, see Cotten et al. 2012). Like these studies, this investigation examines depressive symptomatology as a primary outcome. The HRS measures depression using an 8-item version of the CES-D, which asks if in the past week respondents felt depressed, if they felt as if everything was an effort, if their sleep was restless, if they were happy, if they were lonely, if they enjoyed life, if they felt sad, and if they could not get going. Responses were recoded so that 0 = no and 1 = yes and the responses for the "happy" and "enjoyed life" items were reverse-coded to match the other items. A depression score is calculated for each respondent by adding together the individual items, giving a possible score range of 0-8 with higher scores indicating increased depressive symptomatology. Depression scores are calculated across five waves (2004-2012), with α ranging between .800 and .816 (depending on the wave).

In addition to depressive symptoms, the analyses include outcomes of subjective mental well-being previously summarized in the literature review, including life satisfaction, loneliness, personal growth, and purpose in life. Life satisfaction is measured using a single question that estimates overall satisfaction with life. Respondents in the HRS were asked, "Please think about your life as a whole. How satisfied are you with it?" Possible responses included not at all satisfied, not very satisfied, somewhat satisfied, very satisfied, and completely satisfied. These responses were recoded on a scale of 0-4 with higher scores indicating increased satisfaction. Life satisfaction is measured in three waves (2008-2012). However, as detailed later in this chapter, only the 2008 and 2012 waves are used in the analysis.

Loneliness is measured using a 3-item measure developed by Hughes et al. (2004). Respondents are asked, "How much of the time do you feel…you lack companionship?...left out?...isolated from others?" Scores are recoded such that 0 = hardly ever or never, 1 = some of the time, and 2 = often. An overall score for loneliness is created by averaging the responses. Scores were not calculated for respondents who answered less than two of the loneliness questions. Final scores range from 0-2, with higher scores indicating increased feelings of loneliness. Loneliness was measured across five waves in the HRS (2004-2012), with α ranging from .803 to .817 depending on the wave.

Both personal growth and purpose in life are measured using Ryff's scales of psychological well-being (Keyes, Shmotkin, and Ryff 2002; Ryff 1995; Ryff and Keyes

1995; Ryff and Singer 1998). For both measures, respondents were given a series of statements that they may agree or disagree with (recoded on a 6-point scale, with 0 = strongly disagree and 5 = strongly agree). For personal growth, the items were: “I am not interested in activities that will expand my horizons,” “I think it is important to have new experiences that challenge how I think about myself and the world,” When I think about it, I haven’t really improved much as a person over the years,” “I have the sense that I have developed a lot as a person over time,” “I do not enjoy being in new situations that require me to change my old familiar ways of doing things,” “I gave up trying to make big improvements in my life a long time ago,” and “For me, life has been a continuous process of learning, changing, and growth.” Appropriate responses are reverse-coded such that higher scores indicate increased positive feelings of personal growth. A final score for personal growth is calculated by averaging the scores for the seven responses, giving a final personal growth score that ranged from 0-5. Personal growth scores were not calculated for those with missing data on more than three personal growth items. It should be noted that personal growth was measured *only* in the 2006 survey, with an α of .755.

For purpose in life, the items used in the HRS included: “I enjoy making plans for the future and working to make them a reality,” “My daily activities often seem trivial and unimportant to me,” “I am an active person in carrying out the plans I set for myself,” “I don’t have a good sense of what it is I’m trying to accomplish in life,” “I sometimes feel as if I’ve done all there is to do in life,” “I live life one day at a time and don’t really think about the future,” and “I have a sense of direction and purpose in my life.” Appropriate responses were reverse-coded such that higher scores indicate elevated feelings of purpose in life. Final purpose in life scores are calculated by averaging the seven individual scores together, giving a final score range of 0-5. Purpose in life was measured across four waves (2006-2012), with α ranging from .739-.776.

The primary predictor for the proposed investigation is ICT use, operationalized in the HRS as overall Internet use. Respondents were asked "Do you regularly use the World Wide Web, or the Internet, for sending and receiving e-mail or for any other purpose, such as making purchases, searching for information, or making travel reservations?" Responses were recoded such that 0 = no and 1= yes. Internet use is measured from 2004-2012.

The mediators for this investigation include three conceptualizations of social integration and one conceptualization of social support, all of which were measured from 2004-2012 (Schuster, Kessler, and Aseltine 1990; Turner, Frankel, and Levin 1983). As previously mentioned, social integration has been operationalized in past studies in a number of ways. In the HRS, social integration is measured as composition of social network, number of close social relationships, and contact with social network. Composition of social network is determined by asking respondents the following four questions: "Do you have a husband, wife, or partner with whom you live," "Do you have any living children," "Do you have any other immediate family, for example, any brothers or sisters, parents, cousins or grandchildren," and "Do you have any friends?" Scores are recoded such that 0 = no and 1 = yes. A total score for composition of social network is calculated by summing responses (range 0-4).

The second integration conceptualization is number of close relationships. Respondents were asked: "How close is your relationship with your spouse of partner," "How many of your children would you say you have a close relationship with," "How many of these family members would you say you have a close relationship with," and "How many of your friends would you say you have a close relationship with?" Responses for the first item were recoded such that 0 = not at all close, 1 = not very close, 2 = quite close, and 3 = very close. The responses for the other three items were recoded such that responses from 0-10 retained their numeric value, while any value higher than 10 close relationships was recoded as 10. The four close relationships items are examined as potential mediators separately.

A final measure of social integration is contact with social network. Nine items are used in the HRS. Respondents are asked how often they meet up, speak on the phone, and write/email with three different groups: children, other family (besides spouse), and friends. Responses are recoded such that 0 = less than once a year or never, 1 = once or twice a year, 2 = every few months, 3 = once or twice a month, 4 = once or twice a week, and 5 = three or more times a week. For each group (children, family, friends), the scores for the three separate contact questions (meet up, speak on phone, write/email) are averaged. Each group is examined separately as a potential mediator.

The final mediator is social support. In the HRS, both positive and negative social support are measured; for this investigation, because the theoretical emphasis has been placed on positive aspects of social relationships, positive social support is used only. Three questions are asked of each respondent across four relationship groups (spouse, children, family, friends): "How much do they really understand the way you feel about things," "How much can you rely on them if you have a serious problem," and "How much can you open up to them if you need to talk about your worries?" Responses are recoded such that 0 = not at all, 1 = a little, 2 = some, and 3 = a lot. For each relationship group, the scores of the three questions are averaged and examined as a potential mediator. As with the social integration measures, social support is measured from 2004-2012 with α ranging from .796-.815.

Of note is that while the social integration and social support measures were included in the HRS surveys from 2004-2012, these questions were not asked of all respondents in each year. In 2004 the questions were posed only to a subset of respondents. In following waves the questions were posed only to approximately half of the overall HRS sample and done so in alternating years (e.g., half of the respondents got the questions in 2006 and 2010 while the other half got them in 2008 and 2012). This means that there is only a small subset of individuals in the HRS with 3 waves of social integration/social support data; none have more than 3 as of 2012. As explained later, the longitudinal analytic procedure proposed can account for "missing data" so long as there are respondents with at least 3 time points of data; however, for some outcomes there are no individuals with 3 time points (i.e., the outcome is not measured in 2004) thus preventing longitudinal analysis.

In addition to the primary predictor and mediators, demographic variables were also incorporated into the analysis to determine if controlling for these characteristics helped predict the outcomes. Demographic measures that were used included sex (0 = male, 1 = female), years of education, race (0 = white, 1 = non-white), income (separated into brackets of $10,000 such that 0 = income between $0-$9,999 and 10 = $100,000 or higher), employment status (0 = unemployed, 1 = employed), self-rated health (5 point scale with 0 = poor, 1 = fair, 2 = good, 3 = very good, and 4 = excellent health), and functional limitations (recoded such that 0 = low limitations i.e., less than 3, and 1 = high limitations i.e., 3 or more limitations).

Analytic Procedures

Due to limitations regarding the data available in each wave of the HRS, it is unfortunately impossible to carry out the same analytic procedure for each outcome proposed. While a longitudinal investigation using five waves of data is possible when investigating the effects of ICT use on depression and loneliness, only three waves are available for life satisfaction and purpose in life (and not all waves can be used in the same analysis, as will be explained later in this section). In addition, because the personal growth outcome is measured only in one wave of the HRS, a longitudinal analysis cannot be done. Thus for this study, longitudinal analysis was done for the depression and loneliness outcomes only; cross-sectional analysis was done for life satisfaction, personal growth, and purpose in life.

Longitudinal Analysis

Growth curve modeling is a longitudinal procedure that allows for modeling within-person systematic change and between-person differences over time, and growth curve models can include both time-variant and time-invariant predictors (for a review, see Shek and Ma 2011). Generalized linear models, such as analysis of variance (ANOVA) or analysis of covariance (ANCOVA) can be used to investigate changes over time, but these procedures have limitations, including an increase of Type I errors (i.e., an incorrect rejection of a null hypothesis and acceptance of an alternative hypothesis) if an unbalanced repeated measures design (i.e., study design with missing data and/or with time-varying covariates) is used and an increase in biased standard errors from non-independent observations (Shek and Ma 2011; Singer and Willett 2003). Growth curve modeling allows for examining change over time while accounting for these limitations. A particular strength of this procedure is its ability to account for time-variant and time-invariant independent variables; models can thus successfully include primary predictors and potential mediators regardless of whether or not these variables change over time (Shek and Ma 2011). Because of this, growth curve modeling is used as the primary technique to investigate changes in depression and loneliness.

Growth curve modeling, while an accepted procedure used to investigate change over time, is typically used to examine how predictors influence the trajectories of specific dependent variables; mediation testing has previously involved including potential mediating variables as controls, thus allowing researchers to determine if mediators could act as predictors but did not actually show whether the mediators *mediated* anything (i.e., they do not show if changes in the primary predictor and the overall mediated effect is statistically significant). However, recently procedures have been adopted to allow for mediation testing in hierarchal linear models (such as individual growth curve models). An example is given by Bauer, Preacher, and Gil (2006) wherein the indirect effects of the predictor on the outcome (e.g., the mediated effect) and the total effect (e.g., the overall effect including the mediated effect as well as a direct effect of the predictor on the outcome) are estimated through the use of stacked variables. As outlined by Bauer et al. (2006) and the UCLA Institute for Digital Research and Education (at http://www.ats.ucla.edu/stat/spss/faq/ml_mediation2.htm), the dependent variable is combined with the mediator into one single stacked variable such that one single growth model can be run to determine effects estimates and their variances/covariances. These estimates can then be used to estimate the indirect and total effects of the predictor on the outcome. For more information on the equations used to estimate the indirect and total effects, see Bauer et al. 2006. For this study, an online tool provided by Bauer was used to calculate the indirect and total effects from the growth curve output; this tool can be found at http://www.unc.edu/~dbauer/manuscripts/SPSSEffectsCalc.xls. Significant findings in the growth curve models indicate the predictors included in the model predict the outcome; significant results in the mediation testing for the indirect effect shows that mediation is occurring. If the indirect *and* total effects are found to be significant in the mediation testing, then the mediation that is occurring is partial.

Table 3.1: Descriptive Statistics for Longitudinal Sample (HRS 2004)

Predictor	% or Mean (SD)
Age	74.7 (7.1)
Female	58.4%
Years of Education	12.2 (3.1)
Non-white	14.4%
Income	
$0-$19,999	32.6%
$20,000-$39,999	32.2%
$40,000-$59,999	15.5%
$60,000-$79,999	7.6%
$80,000-$99,999	4.0%
$100,000+	8.1%
Employed	19.5%
Fair or poor health	29.9%
High functional limitations	43.7%
Internet user	25.5%
Depressive symptomatology	1.4 (1.9)
Loneliness	0.4 (0.5)

Mean scores (with standard deviations in parentheses) or percentage of sample with particular attributes are presented.

Table 3.1 contains descriptive statistics for the analytic sample used in the longitudinal analyses (i.e., for the depression and loneliness chapters). For this table the descriptives are limited to values given by HRS respondents from the first wave (2004) for ease of interpretation. For this sample the average age of HRS respondents was around 75. A majority of respondents were female, white, unemployed, in good health, and with low functional limitations. The average number of years of education was slightly over 12, and most reported that their income was below $40,000 per year. Of note is that in 2004 only 26% of HRS respondents in the sample reported using the Internet. The mean levels of depression and loneliness appear to be relatively low for this sample.

Cross-Sectional Analysis

For life satisfaction, while the outcome was measured at 3 time points there are no individuals in the sample that have 3 time points worth of mediation data – at most, respondents could have 2 waves of mediation data from 2006 and 2010. As such, longitudinal analysis is not possible. Because of this, to investigate the relationship between ICT use and well-being for this outcome, a cross-sectional analytic technique is used: ordinary least-squares (OLS) regression. The mediation analysis for this outcome is carried out using the procedures discussed by Baron and Kenny (1986) and consists of three regression models. In the first model, the mediators are regressed on the independent variable (i.e., the social integration and support measures are regressed on the Internet use variable) to determine if a significant relationship exists between the predictor and mediators. In the second model, the outcome is regressed on the independent variable (i.e., personal growth is regressed on Internet use) to determine if a significant relationship exists between the predictor and dependent measure. In the final model, the outcome is regressed simultaneously on the predictor and mediators (i.e., personal growth is regressed on Internet use, social integration, and social support). Significant findings in all three models provide evidence to support the mediation hypotheses. Should Internet use be a significant predictor of life satisfaction in the second model but not the third, then the findings would suggest that social integration and support completely mediate the relationship between the predictor and outcome. If, however, Internet use is found to still be a significant predictor of personal growth in the final model, then the results would suggest that social integration and support act only as partial mediators. A final model is also run incorporating demographic measures, including previous levels of life satisfaction (thus allowing for *some* longitudinal data in the analysis).

Personal growth only has one wave of data available and as such OLS regression is used to test for mediation, similar to the life satisfaction analysis. For purpose in life, similar restrictions on the mediators prevent the analysis from adequately incorporating longitudinal methodology. Since there are 4 surveys in the HRS which contain purpose in life data it is possible to have two sub-samples: a 2006/2010 sample (which includes individuals which have mediator data from the 2006 and 2010 surveys) and a 2008/2012 sample (which includes individuals which have mediator data from 2008 and 2012). For purpose in life, OLS regressions are performed for *both* groups separately. Table 3.2 contains descriptive statistics for the life satisfaction, personal growth, and (both) purpose in life sub-samples. Again, statistics are from the 2004 wave for ease of comparison. While each outcome requires a different sub-sample of the HRS, comparison of the demographic values show that each sample is relatively similar with minor deviations; these samples are also similar to the large sample used in the longitudinal investigation. In examining the scores for the outcomes, it appears that HRS respondents enjoy relatively high scores in life satisfaction, personal growth, and purpose in life.

Table 3.2: Descriptive Statistics for Cross-Sectional Samples

Predictor	Life Satisfaction Sample	Personal Growth Sample	Purpose in Life Sample (2006/2010)	Purpose in Life Sample (2008/2012)
Age	72.3 (5.6)	74.1 (6.6)	72.9 (5.8)	72.0 (5.3)
Female	59.7%	58.9%	58.6%	58.7%
Years of Education	12.5 (3.0)	12.4 (3.0)	12.6 (2.9)	12.6 (3.0)
Non-white	14.6%	13.1%	12.7%	12.7%
Income				
$0-$19,999	26.1%	29.1%	25.4%	23.8%
$20,000-$39,999	32.5%	32.6%	32.6%	33.4%
$40,000-$59,999	16.9%	15.8%	16.7%	18.2%
$60,000-$79,999	9.4%	8.5%	9.3%	9.7%
$80,000-$99,999	4.8%	4.8%	5.1%	4.5%
$100,000+	10.2%	9.3%	10.9%	10.4%
Employed	25.2%	20.8%	24.4%	25.5%
Fair or poor health	21.4%%	25.2%	20.2%	19.9%
High functional limitations	34.8%	40.1%	35.2%	33.5%
Internet user	32.7%	28.7%	33.0%	34.2%
Life satisfaction	3.0 (0.9)	-	-	-
Personal growth	-	3.5 (0.9)	-	-
Purpose in life	-	-	3.5 (1.0)	3.5 (0.9)

Mean scores (with standard deviations in parentheses) or percentage of sample with particular attributes are presented.

CHAPTER FOUR

DEPRESSIVE SYMPTOMATOLOGY

Previous research has provided evidence of a U-shaped trajectory of depression through the life course, with frequency of self-reported depressive symptoms being highest in early adulthood and late life and lowest in midlife (Clarke et al. 2011; Clarke and Wheaton 2005; Kessler et al. 1992; Miech and Shanahan 2000; Mirowsky 1996; Mirowsky and Ross 1992; Ross and Mirowsky 2008; Schieman et al. 2001). While depressive symptomatology may increase over time for older adults, previous studies have found that age may not be a significant predictor for depression; when controlling for such factors as physical disability, cognitive impairment, and socioeconomic status, among others, the relationship between age and depression disappears (Blazer 2003). In this way depression may not be a direct consequence of the aging process but instead a consequence of physical, mental, and social changes that are likely to occur in old age.

Clarke et al. (2011) found evidence to suggest that having meaningful social roles and being in meaningful social relationships has the potential to promote mental well-being through decreased depressive symptomatology in old age. This study seeks to add to the previous literature and investigate potential differences in depressive symptoms between Internet users and non-users through late life and to determine if measures of social integration and social support mediate this relationship through the use of individual growth curve modeling. Interaction effects will also be investigated between Internet use and demographic characteristics.

Growth Curve Analysis

As recommended by Singer and Willett (2003), growth curve analysis should begin with fitting two unconditional models: the *unconditional means model* and the *unconditional growth model*. In the first, the unconditional means model, the grand mean of the proposed outcome is estimated in the absence of all predictors, including a meaningful time variable. The purpose of fitting this model is to partition outcome variation and to determine if differences in the outcome are the result of within-person or between-person variation. In this way, the unconditional means model provides information on the types of predictors that can be included in future models (i.e., individual-level or group-level predictors).

Model A in Table 4.1 shows the results of fitting the unconditional means model to the HRS data with depressive symptomatology (CES-D score) as the outcome. The intercept, or grand mean, for this model is 1.4970 indicating that, on average, respondents across all selected measurement occasions of the HRS sample reported a relatively low CES-D score (scaled 0-8, with 8 = high number of depressive symptoms). The results also reveal that this value is significantly different from 0 (p<.001). The within-person variance component (1.5774) was significant at the p<.001 level, suggesting the existence of additional level-1 outcome variance; put another way, this indicates that additional variance in initial status can be explained with the addition of individual-level predictors that are time-varying. The significance of the level-2 variance component associated with initial status (2.0299, p<.001) suggests that group-level time-invariant predictors can be added to the model to explain additional variance.

In addition to providing information on the grand mean, the unconditional means model allows researchers to determine the proportion of outcome variation between individuals through the calculation of the intraclass correlation coefficient (ICC). The ICC is calculated by dividing the level-2 variance component (in this case, 2.0299) by the sum of the level-1 and level-2 variance components (in this case, 1.5774 + 2.0299 = 3.6073). The ICC for the unconditional means model wherein depressive symptoms is the primary outcome is calculated to be approximately .5627; this indicates that about 56% of the total variation in depressive symptomatology is due to interindividual differences. In multilevel modeling, it is suggested that if the ICC is less than 25% then growth curve modeling may be an inappropriate modeling procedure (Heinrich and Lynn 2001; Kreft 1996) and simpler procedures, such as ANOVA, may be more appropriate (de Leeuw and Kreft 1995). Based on the results presented in Model A, growth curve modeling is an appropriate method of fitting the HRS data.

The second unconditional model to fit as recommended by Singer and Willett (2003) is the unconditional growth model. The unconditional growth model adds a meaningful measure of time as a predictor of the outcome, and the purpose of the model is to determine if there is any significant linear change in the outcome across individuals across time points. The intercept, rather than estimating the grand mean across all individuals across all measurement occasions, now estimates the mean in the outcome at baseline; in addition, the slope of the trajectory of linear change over time is estimated as a fixed effect. Should no significant relationship be found between time and the outcome, further growth curve modeling would be unnecessary (Shek and Ma 2011).

Time can be operationalized in growth curve modeling in a variety of ways based on the needs of the researcher – time can be a function of survey wave (i.e., time point 1 = survey 1, time point 2 = survey 2, etc.) or a function of age (i.e., time point 1 = 65 years,

Table 4.1: Fitting Alternative Polynomial Change Trajectories to CES-D Scores

		Model A *No change*	Model B *Linear change*	Model C *Quadratic change*	Model D *Cubic change*
Fixed Effects	Intercept	1.4970***	1.4307***	1.4034***	1.3932***
	AGE75 (linear term)		0.0242***	0.0194***	0.0217***
	AGE75^2 (quadratic term)			0.0009***	0.0013***
	AGE75^3 (cubic term)				-0.0000
Variance Components					
Level 1:	Within-person	1.5774***	1.5195***	1.5174***	1.5176***
Level 2:	In initial status	2.0299***	1.8995***	1.8950***	1.8963***
	In rate of change		0.0045***	0.0046***	0.0046***
	Covariance		-0.0073*	-0.0071*	-0.0070*
Goodness-of-fit					
	Deviance	135774.6	135502.3	135481.8	135478.5
	AIC	135780.6	135514.3	135495.8	135494.5
	BIC	135806.1	135565.3	135555.3	135562.5

*p<.05; **p<.01; ***p<.001
N = 9414

time point 2 = 66 years, etc.). The measure of time used in the unconditional growth model for depressive symptoms is *AGE75*, computed by taking each HRS respondent's age and subtracting 75. Constructing the time variable in this manner centers the interpretation of the model's intercept at 75; put another way, the value of the intercept will now represent the mean CES-D score for a 75 year-old HRS respondent. Centering time in this manner complicates the interpretation of the intercept as the youngest members of the sample, those aged 65, are no longer the baseline for interpretation; however, centering age in this way helps avoid multicollinearity should other measurements of time (i.e., a quadratic or cubic measure of time) be included in future models. Age 75 was selected as baseline or centering point as this is often used as a distinction between the young-old and the old-old in aging research.

Model B in Table 4.1 presents the fitted model wherein *AGE75* is included as a predictor. As stated previously, the intercept is now interpreted as the average CES-D score for an HRS respondent who is 75 years of age. The intercept value is 1.4307 (p<.001) indicating that the average 75 year-old HRS respondent had a relatively low CES-D score, smaller than the grand mean of all HRS respondents across all measurement occasions estimated in Model A. The *AGE75* fixed effects estimate presents the slope of change in CES-D scores over time assuming that the change is linear. The term, 0.0242, indicates that with each additional year of age an HRS respondent's CES-D score will increase on average by 0.0242 points in the 8-point scale. The magnitude of this change over time is relatively small – to put it in perspective, at this rate of change it would take over 40 years for the average HRS respondent's CES-D score to increase by a full point. That said, the linear term was found to be significantly different from 0 (p<.001), indicating that this change over time, while small, is significant.

The within-person variance component decreased between Model A and Model B, indicating that variability at the individual level was at least partly explained by the inclusion of time; however, the component is still significantly different from 0 (p<.001) and suggests that additional time-varying predictors can be added to the model and explain additional variance. The level-2 variance components assess variability in true initial status (1.8995) and variability in true rates of change (0.0045); as both are found to be significantly non-zero (p<.001), time-invariant predictors can be added in future models to explain additional variance. The covariance, or correlation between the intercept and the linear growth parameter, was estimated to be -0.0073 (p<.05). The advantage of the covariance parameter is that it allows researchers to determine if those with a high outcome score at baseline experience change in the outcome more or less rapidly over time. The negative value found in Model B suggests that HRS respondents who were 75 and had a high CES-D score experienced less rapid growth in CES-D scores over time compared to those with lower scores at age 75.

While the unconditional growth model allows for researchers to determine if significant change in an outcome occurs over time, a weakness of the model is that the estimates assume a linear trajectory in the outcome. This is problematic, as not all outcomes change in a linear fashion. Depressive symptomatology is one such outcome, as previous research has shown that depressive symptoms do not increase linearly in later life (Clarke et al. 2011; Clarke and Wheaton 2005; Kessler et al. 1992; Miech and Shanahan 2000; Mirowsky 1996; Mirowsky and Ross 1992; Ross and Mirowsky 2008; Schieman et al. 2001). As such, it is important to test alternative polynomial models that account for non-linear change trajectories. This can be done by introducing a quadratic measure of time ($AGE75^2$) and a cubic measure of time ($AGE75^3$). Model C introduces the quadratic term while Model D introduces the cubic term.

Inclusion of the quadratic term in Model C does little to the estimates for the intercept and linear change term. On average, a 75 year old will have a CES-D score of 1.4034 and will increase by approximately 0.0194 points with e ach additional year of age. The quadratic estimate, while small in magnitude, is positive and significant ($p<.001$). This result suggests that over time the *rate of growth* in depressive symptomatology increases and that the trajectory of depressive symptoms over time may be curved rather than linear. The introduction of the cubic term in Model D does not change the magnitude or significance level of the other fixed effects. The cubic term is negative, suggesting that the acceleration in rate of growth decreased over time (i.e., leveled-off). However, it is important to note that the cubic term in Model D was not found to be significantly different from 0, suggesting that this decrease in accelerated growth was almost non-existent.

In addition to presenting the fixed effects of the intercept and time variables as well as the variance components, Table 4.1 includes goodness-of-fit tests. These tests evaluate the overall fit of the model and help researchers determine if more variables should be included or if variables should be taken out. For the three tests presented (deviance, AIC, and BIC) the statistics will decrease as the models are better fit; increases between models suggest that the variables that are added do not improve overall model fit and the researcher should consider taking them out completely. As can be seen in Table 4.1, all three goodness-of-fit statistics decreased from Model A to Model B and then again from Model B to Model C. Between Model C and D both the deviance statistic and the AIC statistic decreased, however the BIC statistic increased. This, coupled with the finding that the cubic term in Model D was not significantly different from 0, suggests that the cubic term should be excluded from all future models. As such, from this point forward only *AGE75* and $AGE75^2$ will be included when fitting models to the HRS data wherein depressive symptomatology is the outcome.

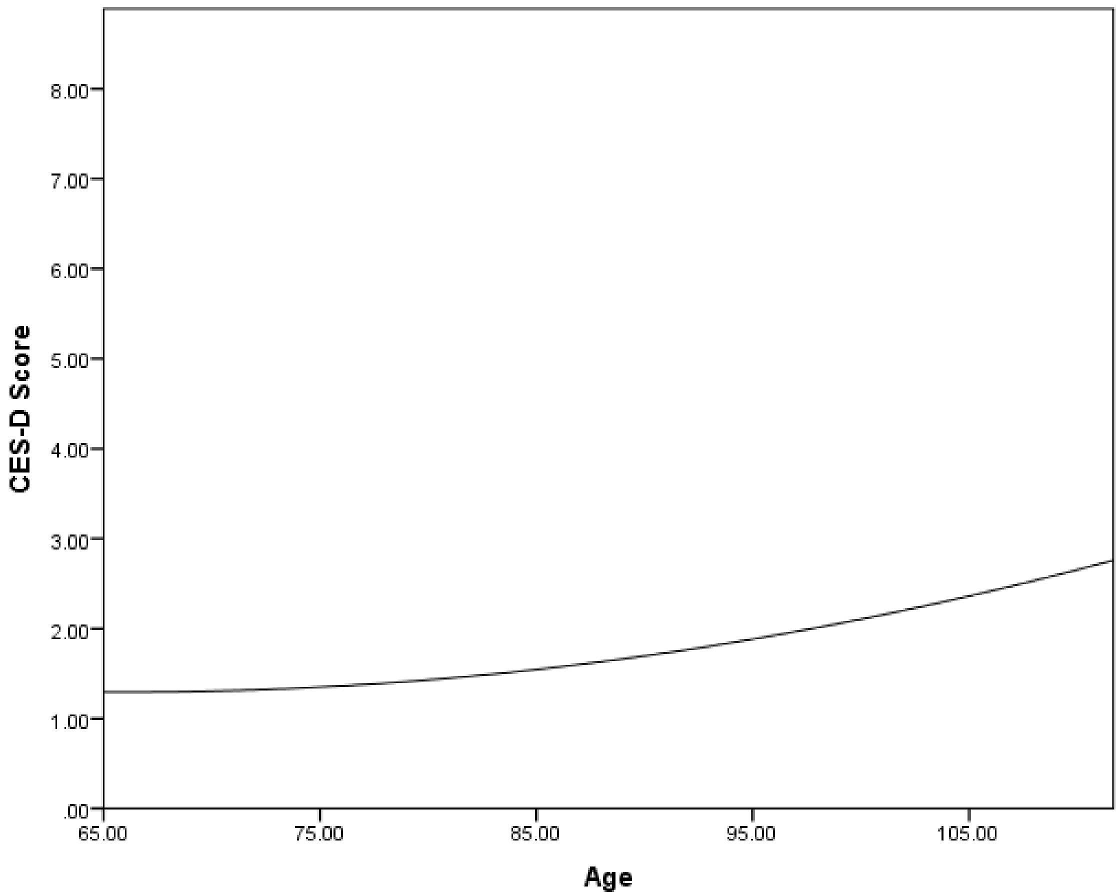

Figure 4.1: Fitted Line of CES-D Scores by Age

The finding that CES-D growth is non-linear for the HRS sample is not surprising given previous research suggesting a curved growth later in life. Figure 4.1 plots a fitted line to CES-D scores by age. As can be seen, CES-D scores gradually increase over time but by very small increments, and the rate of change increases later in life. This visual representation supports what was found in the growth models presented in Table 4.1. In summary, based on the initial growth models as well as Figure 4.1, support was found for Hypothesis 1 at least with regards to the outcome of depressive symptomatology; depressive symptoms increase over time.

With the unconditional means model, unconditional growth model, and models fitting higher polynomials complete, predictors are added to investigate what variables affect depressive symptoms in old age and to determine if any of these measures have an effect over time. Table 4.2 shows the results of these growth models. Model E begins with the addition of the main predictor, Internet use (abbreviated as *INTERNET* in the table). *INTERNET* is added without an interaction with the time variables to determine, first, what the main effect of *INTERNET* is on CES-D scores. The coefficient presented in Model E (-0.03636, $p<.001$) shows that there is a negative relationship with *INTERNET* and initial status in depressive symptomatology. In summary, Internet users reported significantly lower CES-D scores compared to non-users. Comparison of the goodness-of-fit statistics between Model E and the models presented in Table 4.1 show that all statistics (deviance, AIC, BIC) decreased, indicating that the addition of *INTERNET* improved overall model fit. Taken together, Model E suggests that *INTERNET* is a significant predictor of CES-D scores. Support is found for Hypothesis 2 with regards to the outcome of depressive symptomatology.

While Model E reveals the main effect of *INTERNET* on depressive symptoms, it does not indicate if *INTERNET* predicts change over time. Does *INTERNET* affect the trajectory of depressive symptoms? It was hypothesized that Internet users, compared to non-users, would experience fewer depressive symptoms over time such that the gap in

CES-D scores would grow as HRS respondents aged. Model F tests this hypothesis by including interactions between *INTERNET* and both time measures that were significant in Table 4.1 (linear term *AGE75* and quadratic term $AGE75^2$). Results reveal that there was no significant relationship between *INTERNET* and time in the HRS sample.

While Internet users, compared to non-users, do report lower CES-D scores across time points, the gap does not significantly grow. This is supported by a visual representation of the data in Figure 4.2 – both Internet users and non-users experience increases in CES-D scores over time and Internet users characteristically have lower scores, however the gap between the two groups does not appear to change in a noticeable manner. Support is not found for Hypothesis 3, which suggests that Internet use will predict significant change in depressive symptoms over time. Because no significant interaction is found between *INTERNET* and the time variables, the interactions are removed from future models to improve model fit.

Model G incorporates demographic characteristics without interactions with the time variables. In summary, being female and having more functional limitations were significantly associated with increased CES-D scores while being more educated, having more income, being employed, and having increased self-rated health were significantly associated with lower CES-D scores ($p<.001$). Interestingly, inclusion of the demographic characteristics explains the effect of *AGE75*, as there is no significant relationship between *AGE75* and CES-D scores in Model G. This supports previous literature that suggests that there is no direct relationship between age and depression, and that depression in old age is the result of other factors that change later in life (Blazer 2003). *INTERNET* remained a significant predictor of depressive symptoms ($p<.001$).

Inclusion of these demographic predictors substantially increased model fit as there was a large decrease in deviance, AIC, and BIC.

Model H adds interactions between the demographic variables and time variables. Significant interactions were found with sex and functional limitations. Sex was found to have a significant relationship with the quadratic term but surprisingly not the linear term. This suggests that while it appears that the gap in CES-D scores increases over time between men and women (with women reporting higher scores), this change in gap size is not significant; however, the *rate in growth of the gap* significantly decreases over time. With regards to functional limitations, a significant negative relationship was found with the linear term, suggesting that the gap between those with high limitations and those with low limitations decreased over time. No significant interaction was found between functional limitations and $AGE75^2$. In summary, while the inclusion of the demographic characteristics improved model fit, most of these measures did not have a significant effect on depressive symptomatology over time. In addition, *INTERNET* still retained a significant relationship with CES-D scores, even when controlling for the interactions between demographics and time.

Moderation Testing

In addition to examining the effects of *INTERNET* while controlling for demographic characteristics, interactions between *INTERNET* and the other measures were examined individually to determine if any of the demographic characteristics act as potential

Table 4.2: Fitting Change Trajectories with Internet Use to CES-D Scores

		Model E *Main effect of INTERNET*	Model F *INTERNET predicting growth*	Model G *Main effect of demographic predictors*	Model H *Growth and demographic predictors*
Fixed Effects	Intercept	1.5119***	1.5145***	2.6214***	2.5859***
	AGE75	0.0175***	0.0175***	-0.0037	-0.0010
	AGE75^2	0.0007***	0.0007**	0.0008***	0.0017
	INTERNET	-0.3636***	-0.3745***	-0.1098***	-0.1056***
	INTERNET x *AGE75*		0.0008		
	INTERNET x *AGE75*^{2}		0.0003		
	SEX			0.2796***	0.3340***
	SEX x *AGE75*				0.0004
	SEX x *AGE75*^{2}				-0.0013**
	EDUCATION			-0.0515***	-0.0525***
	EDUCATION x *AGE75*				0.0005
	EDUCATION x *AGE75*^{2}				-0.0000
	RACE			0.0303	0.0333
	RACE x *AGE75*				-0.0109
	RACE x *AGE75*^{2}				-0.0001
	INCOME			-0.0258***	-0.0236***
	INCOME x *AGE75*				0.0004
	INCOME x *AGE75*^{2}				-0.0001
	EMPLOY			-0.1892***	-0.1876***

	EMPLOY x *AGE75*				-0.0038
	EMPLOY x *AGE75*^{2}				-0.0001
	HEALTH			-0.3975***	-0.3980***
	HEALTH x *AGE75*				-0.0019
	HEALTH x *AGE75*^{2}				-0.0001
	FUNCTION			0.4789***	0.4889***
	FUNCTION x *AGE75*				-0.0103*
	FUNCTION x *AGE75*^{2}				0.0002
Variance Components					
Level 1:	Within-person	1.5207***	1.5206***	1.5101***	1.5108***
Level 2:	In initial status	1.8258***	1.8251***	1.2138***	1.2129***
	In rate of change	0.0045***	0.0045***	0.0025***	0.0023***
	Covariance	-0.0062*	-0.0061*	0.0001	0.0007
Goodness-of-fit					
	Deviance	134993.0	134992.3	111840.8	111813.0
	AIC	135009.0	135012.3	111870.8	111871.0
	BIC	135077.0	135097.3	111995.7	112112.5

*p<.05; **p<.01; ***p<.001
N = 9414

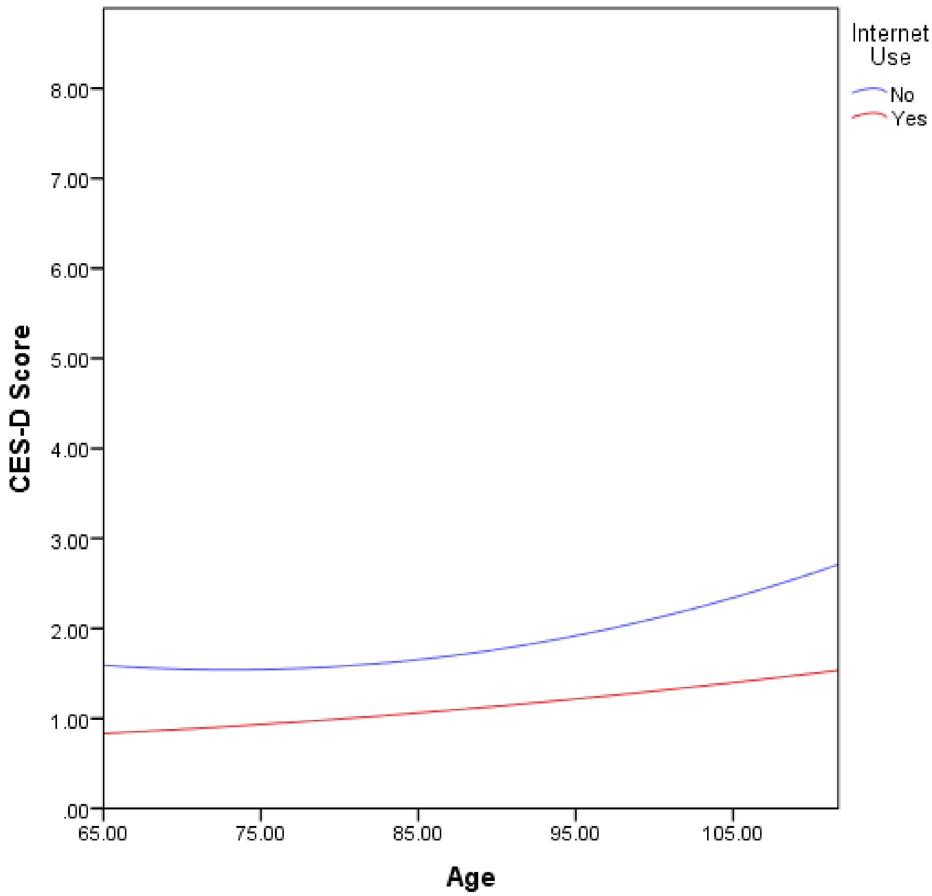

Figure 4.2: Difference in CES-D Scores between Internet Users and Non-Users

moderators between Internet use and CES-D score. While no significant interaction was found for the sex, education, and race measures, a significant relationship was found between *INTERNET* and the variables *INCOME*, *EMPLOY*, *HEALTH*, and *FUNCTION*. The results of these models are presented in Tables 4.3 through 4.6 and Figures 4.3 through 4.7.

Model I in Table 4.3 presents a simplified growth model wherein only previously found significant relationships between *INTERNET*, *INCOME*, and CES-D scores are

Table 4.3: Interactions between *INTERNET* and *INCOME* Predicting CES-D Scores

		Model I *INTERNET and INCOME*	Model J *Main Effects of INTERNET and INCOME Interaction*	Model K *Interaction of INTERNET and INCOME Over Time*
Fixed Effects	Intercept	1.7151***	1.7552***	1.7537***
	AGE75	0.0105***	0.0105***	0.0089**
	AGE75^2	0.0008***	0.0008***	0.0009***
	INTERNET	-0.3140***	-0.4753***	-0.4804***
	INCOME	-0.0655***	-0.0795***	-0.0797***
	INTERNET x *INCOME*		0.0382***	0.0418***
	INTERNET x *INCOME* x *AGE75*			0.0009
	INTERNET x *INCOME* x *AGE75*^{2}			-0.0001
Variance Components				
Level 1:	Within-person	1.5291***	1.5298***	1.5300***
Level 2:	In initial status	1.7760***	1.7654***	1.7653***
	In rate of change	0.0025***	0.0025***	0.0025***
	Covariance	-0.0013	-0.0014	-0.0011
Goodness-of-fit				
	Deviance	115587.2	115563.1	115561.1
	AIC	115605.2	115583.1	115585.1
	BIC	115680.3	115666.4	115685.1

*p<.05; **p<.01; ***p<.001
N = 9414

included. Taking out variables with no significant relationship with the outcome and taking out the other demographic characteristics allows for a less complicated look at the potential moderation effects. This simplified model thus does not include interactions with the linear time term nor the quadratic time term. As shown, both *INTERNET* and *INCOME* are significant predictors of depressive symptomatology such that those who report being Internet users and those who report having higher incomes report lower CES-D scores. Model J incorporates an interaction term between *INTERNET* and *INCOME*. Inclusion of this term changes the interpretation of both the *INTERNET* term as well as the *INCOME* term. *INTERNET* is now interpreted as the difference between Internet users and non-users *among those in the lowest income bracket*. Model J shows that, among those in the lowest income bracket, Internet users on average have lower CES-D scores (p<.001). *INCOME* is now interpreted as differences between income brackets in CES-D scores *among Internet non-users*. As can be seen, those with higher incomes report lower CES-D scores (p<.001). The interaction term was found to be significant (0.0382, p<.001), indicating a significant moderation effect of income on Internet use.

The interaction is best explained using an illustration. Figure 4.3 shows the interaction of *INTERNET* with a simplified version of *INCOME* (in this figure, income is recoded into two categories – high and low, using, $50,000 as the cutoff). As can be seen, across all age groups those who report being Internet users and in a higher income bracket also report the lowest CES-D scores. High income non-users report CES-D scores that are comparable to low income Internet users in younger ages; however, by late life non-using individuals with high income actually have *higher* levels of depressive symptomatology compared to low income Internet users. Low income non-users typically report the highest CES-D scores until late life, in which high income non-users report the highest scores. Examining the trajectories of low income and high income

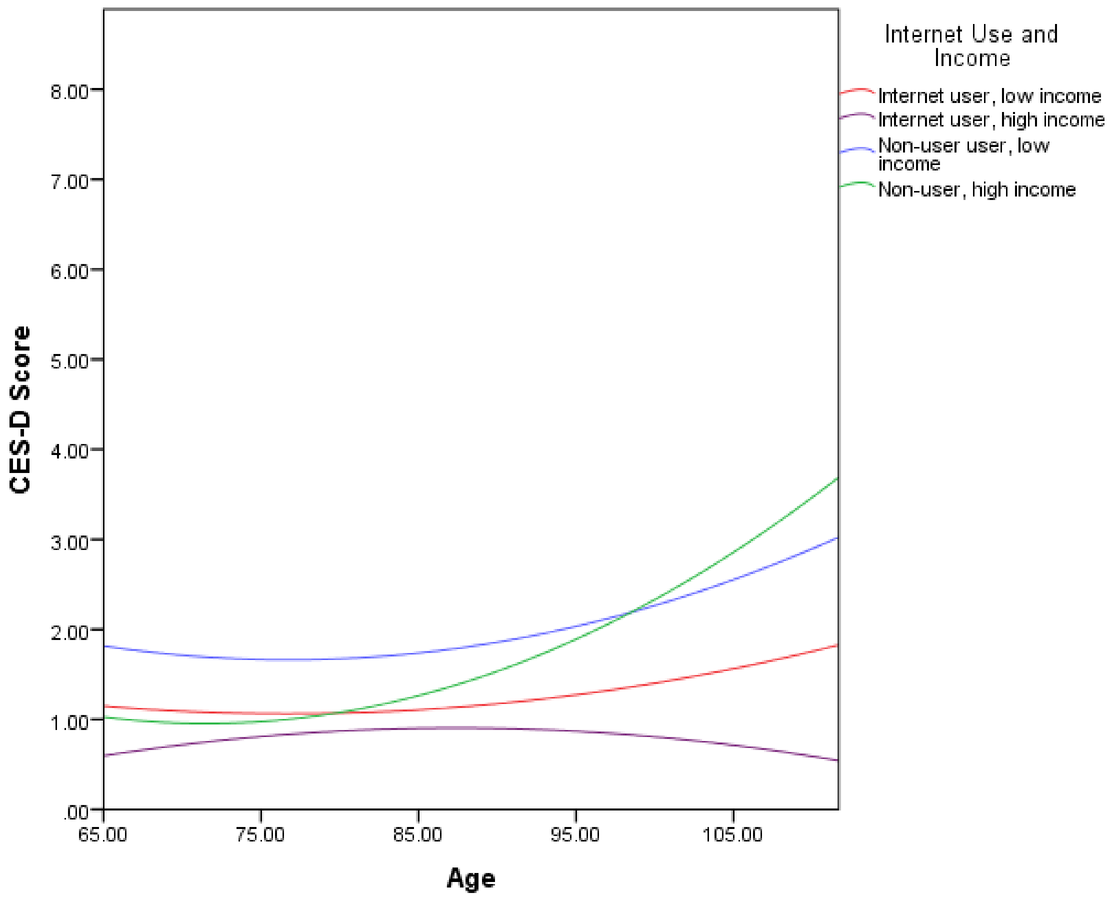

Figure 4.3: Internet Use and Income Predicting CES-D Scores

separately, it can be seen that among those in the lower income brackets, Internet users report lower CES-D scores but the trajectories of growth are strikingly similar – both increase over time but to a relatively small extent. Among those in the high income brackets, however, the difference is striking – users continually report lower CES-D scores and the gap between users and non-users increases over time. The statistics reported in Model J and the visual representation in Figure 4.3 suggest that Internet use affects CES-D scores differently depending on the level of income an individual has.

Table 4.4: Interactions between *INTERNET* and *EMPLOY* Predicting CES-D Scores

		Model L *INTERNET and EMPLOY*	Model M *Main Effects of INTERNET and EMPLOY Interaction*	Model N *Interaction of INTERNET and EMPLOY Over Time*
Fixed Effects	Intercept	1.5709***	1.5788***	1.5785***
	AGE75	0.0108***	0.0107***	0.0104***
	AGE75^2	0.0009***	0.0009***	0.0009***
	INTERNET	-0.3507***	-0.3799***	-0.3803***
	EMPLOY	-0.3837***	-0.4412***	-0.4417***
	INTERNET x *EMPLOY*		0.1498**	0.1624**
	INTERNET x *EMPLOY* x *AGE75*			0.0032
	INTERNET x *EMPLOY* x *AGE75*^{2}			-0.0002
Variance Components				
Level 1:	Within-person	1.5212***	1.5213***	1.5213***
Level 2:	In initial status	1.7836***	1.7812***	1.7810***
	In rate of change	0.0044***	0.0044***	0.0044***
	Covariance	-0.0045	-0.0046	-0.0045
Goodness-of-fit				
	Deviance	134795.4	134787.2	134787.0
	AIC	134813.4	134807.2	134811.0
	BIC	134889.9	134892.2	134912.9

*p<.05; **p<.01; ***p<.001
N = 9414

A final model wherein three-way interactions between *INTERNET*, *INCOME*, and both time variables was run to determine if this interaction significantly changed over time. The results are presented in Model K. Overall, no significant relationship was found between the three-way interactions and the outcome.

Model L in Table 4.4 examines the main effects of *INTERNET* and *EMPLOY* on CES-D scores. This is a simplified model that contains only previously found significant relationships that included *INTERNET* and *EMPLOY*; as such, no interactions are included with time variables (*AGE75* and $AGE75^2$) since neither Internet use nor employment status were found to have significant interactions with the linear or quadratic relationships that included *INTERNET* and *EMPLOY*; as such, no interactions are included with time variables (*AGE75* and $AGE75^2$) since neither Internet use nor employment status were found to have significant interactions with the linear or quadratic terms in previous models. In this model both Internet use and employment are shown to significantly predict CES-D scores ($p<.001$): Internet users, compared to non-users, report lower CES-D scores and those who are employed, compared to those who are not, report lower CES-D scores. Model M includes the interaction between Internet use and employment (this changes the interpretation of *INTERNET* to be differences in CES-D scores between Internet users and non-users among the unemployed, and *EMPLOY* is now interpreted as the difference between the employed and unemployed among Internet non-users) and is found to be significant ($p<.01$). For ease of interpretation, Figure 4.4 presents fitted line trajectories examining this interaction. As can be seen, unemployed Internet non-users report the highest CES-D scores across all time points. The other three groups (unemployed Internet-users, employed Internet users, and employed non-users) all have somewhat similar CES-D trajectories but are all noticeably lower than unemployed non-users. It has been well documented that employment can have significant effects on

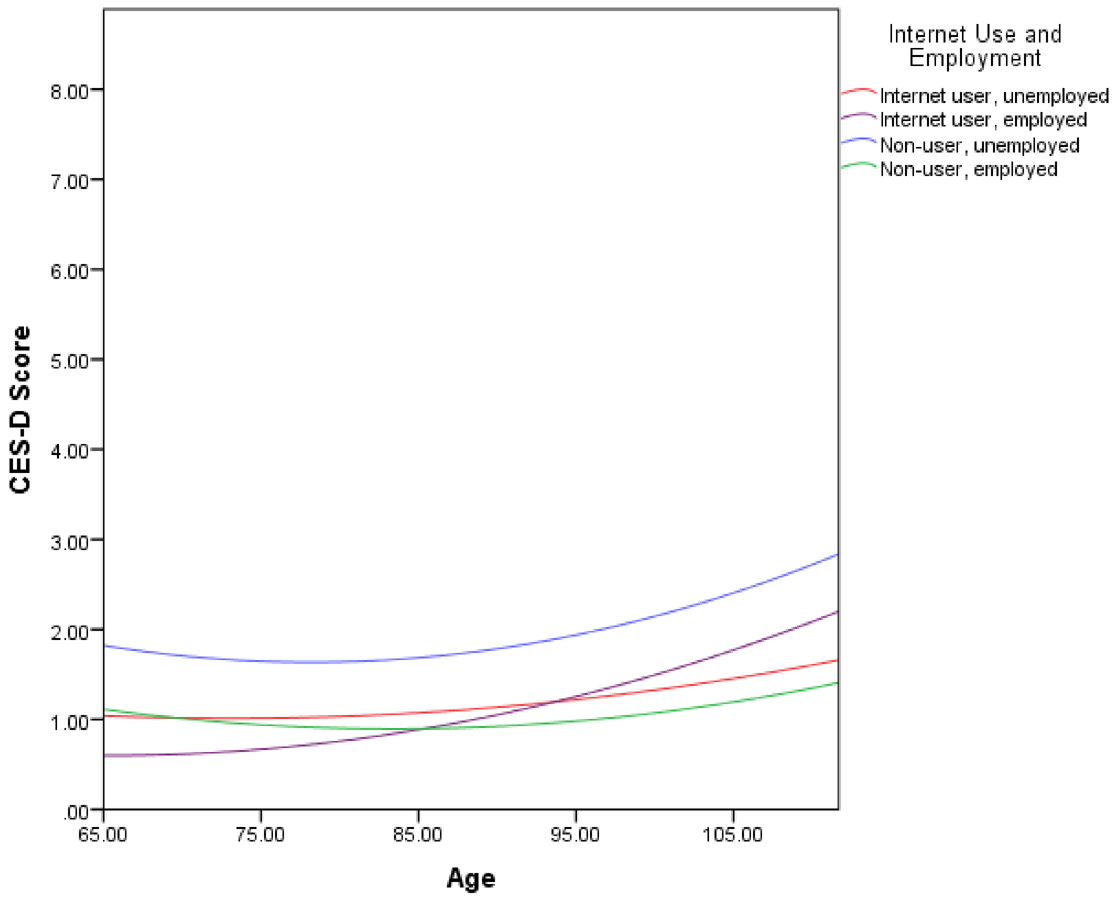

Figure 4.4: Internet Use and Employment Predicting CES-D Scores

the aging population (for example, see Mirowsky and Ross 1992), but this finding suggests that the effects can be more favorable for Internet users. Model N includes three-way interactions with *INTERNET*, *EMPLOY*, and the time variables but none were found to be significant and the inclusion of these interactions was not found to improve overall model fit.

Model O in Table 4.5 simplifies the relationships between *INTERNET*, *HEALTH*, and CES-D scores and includes only associations found to be significant in previous models. As such, no interactions are included between *INTERNET* and the time variables and no

Table 4.5: Interactions between *INTERNET* and *HEALTH* Predicting CES-D Scores

		Model O *INTERNET and HEALTH*	Model P *Main Effects of INTERNET and HEALTH Interaction*	Model Q *Interaction of INTERNET and HEALTH Over Time*
Fixed Effects	Intercept	2.4424***	2.4712***	2.4720***
	AGE75	0.0074***	0.0076***	0.0082**
	AGE75^2	0.0007***	0.0007***	0.0007**
	INTERNET	-0.2678***	-0.4053***	-0.4041***
	HEALTH	-0.4694***	-0.4847***	-0.4846***
	INTERNET x *HEALTH*		0.0608**	0.0582**
	INTERNET x *HEALTH* x *AGE75*			-0.0006
	INTERNET x *HEALTH* x *AGE75*^{2}			-0.0001
Variance Components				
Level 1:	Within-person	1.5129***	1.5136***	1.5135***
Level 2:	In initial status	1.3642***	1.3614***	1.3614***
	In rate of change	0.0036***	0.0036***	0.0036***
	Covariance	-0.0047	-0.0048	-0.0049*
Goodness-of-fit				
	Deviance	132472.0	132462.5	132462.3
	AIC	132490.0	132482.5	132486.3
	BIC	132566.5	132567.5	132588.2

*p<.05; **p<.01; ***p<.001
N = 9414

interactions are included between *HEALTH* and the time variables. In this model both Internet use and self-rated health significantly predict initial status in depressive symptoms: Internet users report lower CES-D scores, and those with higher self-rated

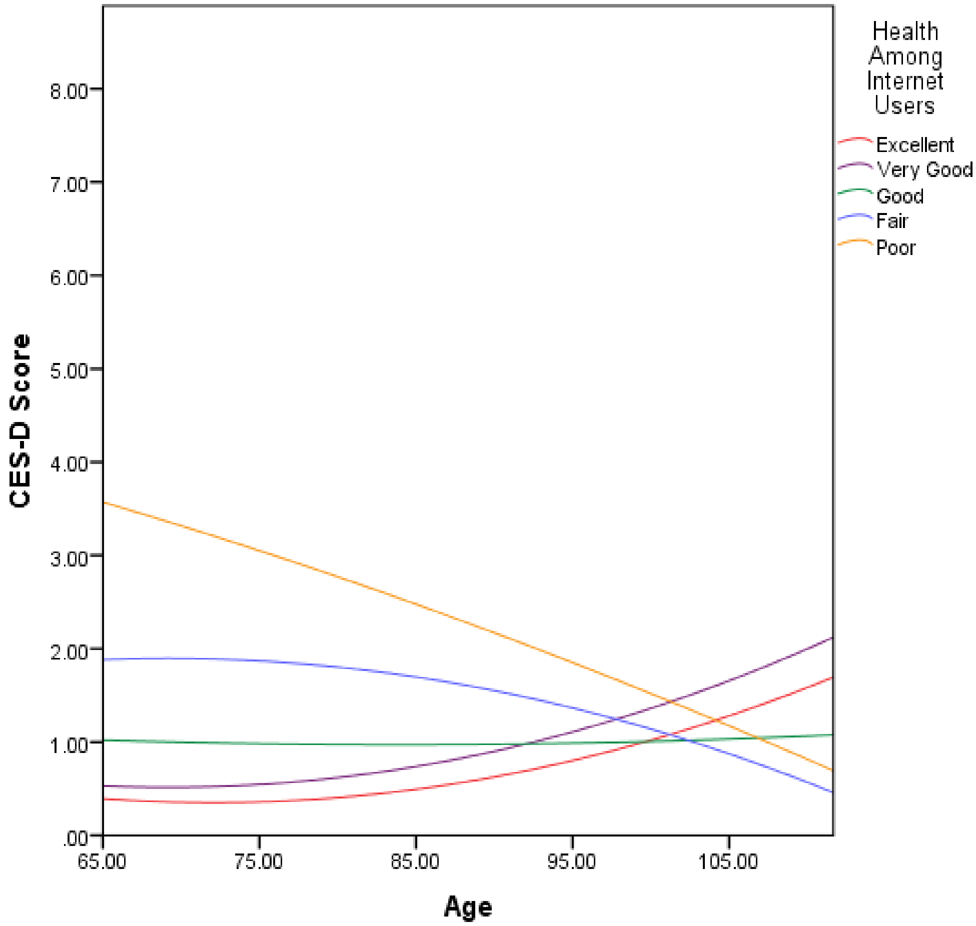

Figure 4.5: Self-Rated Health Predicting CES-D Scores among Internet Users

health report lower CES-D scores. Model P includes the interaction between *INTERNET* and *HEALTH* and shows that there is a significant moderation effect of self-rated health on Internet use (*p*<.01) and is illustrated in Figures 4.5 and 4.6. Among Internet users with fair and poor health, CES-D scores begin much higher compared to those in excellent and very good health and the scores appear to decrease over time; for those in excellent and very good health, CES-D scores appear to increase over time but do not converge with those with lower health scores until very late in life. Among non-users

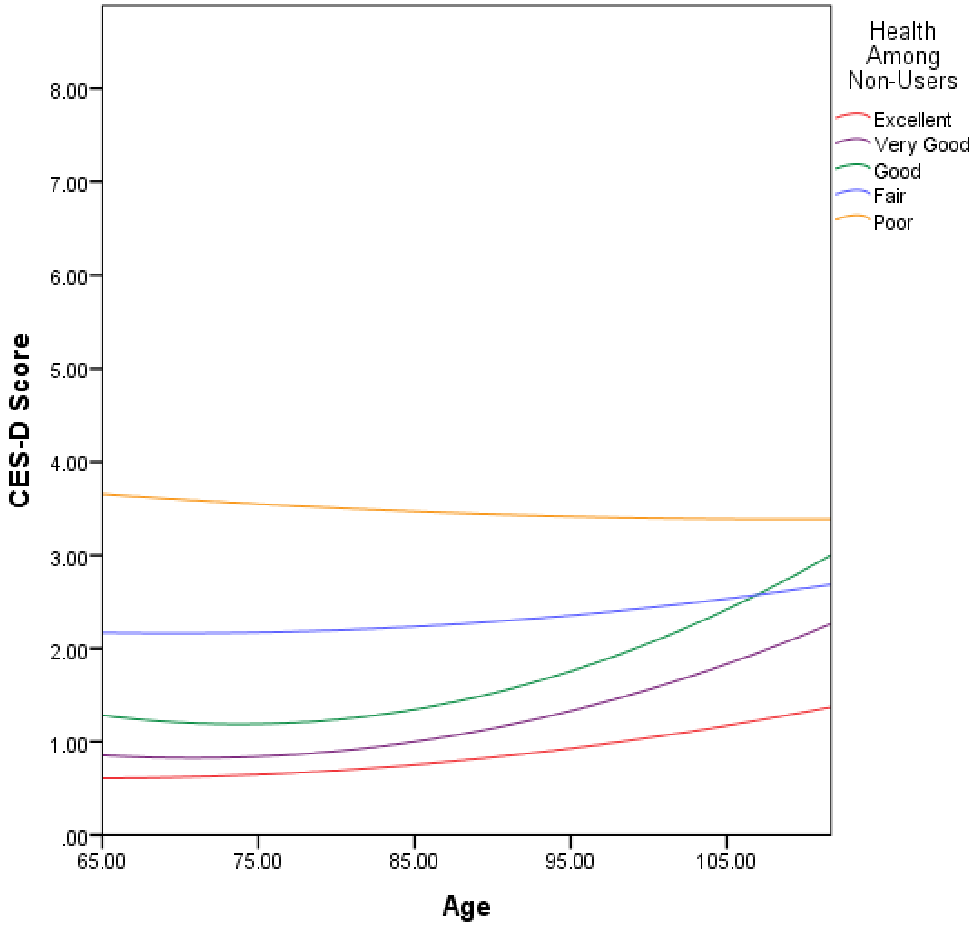

Figure 4.6: Self-Rated Health Predicting CES-D Scores among Internet Non-Users

with poor health, CES-D scores are higher than all other groups across all time points but do appear to decrease over time. However, this decrease is much less steep compared to Internet users in poor health. Another noticeable difference between Internet users and non-users is found when comparing those in fair health: for Internet users CES-D scores decreased over time for those in fair health, but for non-users CES-D scores actually *increased*. Thus it appears that the effect of Internet use on CES-D scores is moderated by health in the sense that Internet users may have more favorable CES-D scores compared to non-users, particularly for those reporting fair and poor health. Model Q includes three-way interactions with *INTERNET*, *HEALTH*, and the time variables, although these interactions were not found to be significant. The increase in goodness-of-fit scores between Models P and Q also suggest that the three-way interactions do not improve the overall modeling of Internet use and self-rated health on depressive symptoms.

Model R in Table 4.6 simplifies the relationship of *FUNCTION* and includes only variables relating to time, Internet use, and functional limitations that were previously found to be significant in earlier models; as such, interactions between *INTERNET* and $AGE75/AGE75^2$ are not included, nor is an interaction between *FUNCTION* and $AGE75^2$. As previously found, *INTERNET* is a significant predictor of CES-D scores such that Internet users have lower scores compared to non-users. In addition, those with more functional limitations have higher CES-D scores, although the gap in depressive symptomatology between those with more limitations and those with fewer closes over time. Model S includes an interaction between *INTERNET* and *FUNCTION*. Inclusion of the interaction term changes the interpretation of the other coefficients. The coefficient for *INTERNET* is now interpreted as the difference in CES-D scores between Internet users and non-users among those who report low functional limitations. On average, Internet users with low functional limitations have lower CES-D scores compared to non-users with low limitations (p<.001). The coefficient for *FUNCTION* is now interpreted as the difference in CES-D scores between those with low and high limitations for Internet non-users. On average, those with more functional limitations

Table 4.6: Interactions between *INTERNET* and *FUNCTION* Predicting CES-D Scores

		Model R *INTERNET and FUNCTION*	Model S *Main Effects of INTERNET and FUNCTION Interaction*	Model T *Interaction of INTERNET and FUNCTION Over Time*
Fixed Effects	Intercept	1.1835***	1.1579***	1.1578***
	AGE75	0.0116***	0.0123***	0.0123***
	AGE75^2	0.0006**	0.0006**	0.0006**
	INTERNET	-0.3222***	-0.2564***	-0.2564***
	FUNCTION	0.7195***	0.7693***	0.7707***
	FUNCTION x *AGE75*	-0.0111***	-0.0126***	-0.0130***
	INTERNET x *FUNCTION*		-0.1688***	-0.1751***
	INTERNET x *FUNCTION* x *AGE75*			0.0016
	INTERNET x *FUNCTION* x *AGE75*^{2}			0.0001
Variance Components				
Level 1:	Within-person	1.5331***	1.5337***	1.5337***
Level 2:	In initial status	1.5003***	1.4949***	1.4946***
	In rate of change	0.0041***	0.0041***	0.0041***
	Covariance	-0.0012	-0.0011	-0.0010
Goodness-of-fit				
	Deviance	133846.2	133829.2	133829.0
	AIC	133866.2	133851.2	133855.0
	BIC	133951.2	133944.6	133965.5

*p<.05; **p<.01; ***p<.001
N = 9414

report higher scores among non-users, although according to the interaction with *AGE75* the gap closes slowly over time (p<.001).

The interaction between *INTERNET* and *FUNCTION* in Model S was significant (p<.001), suggesting a moderating effect of physical functioning on the relationship between Internet use and depressive symptomatology. This interaction is best illustrated in Figure 4.7. Among those with low functional limitations, CES-D scores start small and gradually increase over time. For this group, Internet users have lower scores although the magnitude in difference appears small, and there is no change in the gap over time. An interesting result is found when focusing on HRS respondents with high

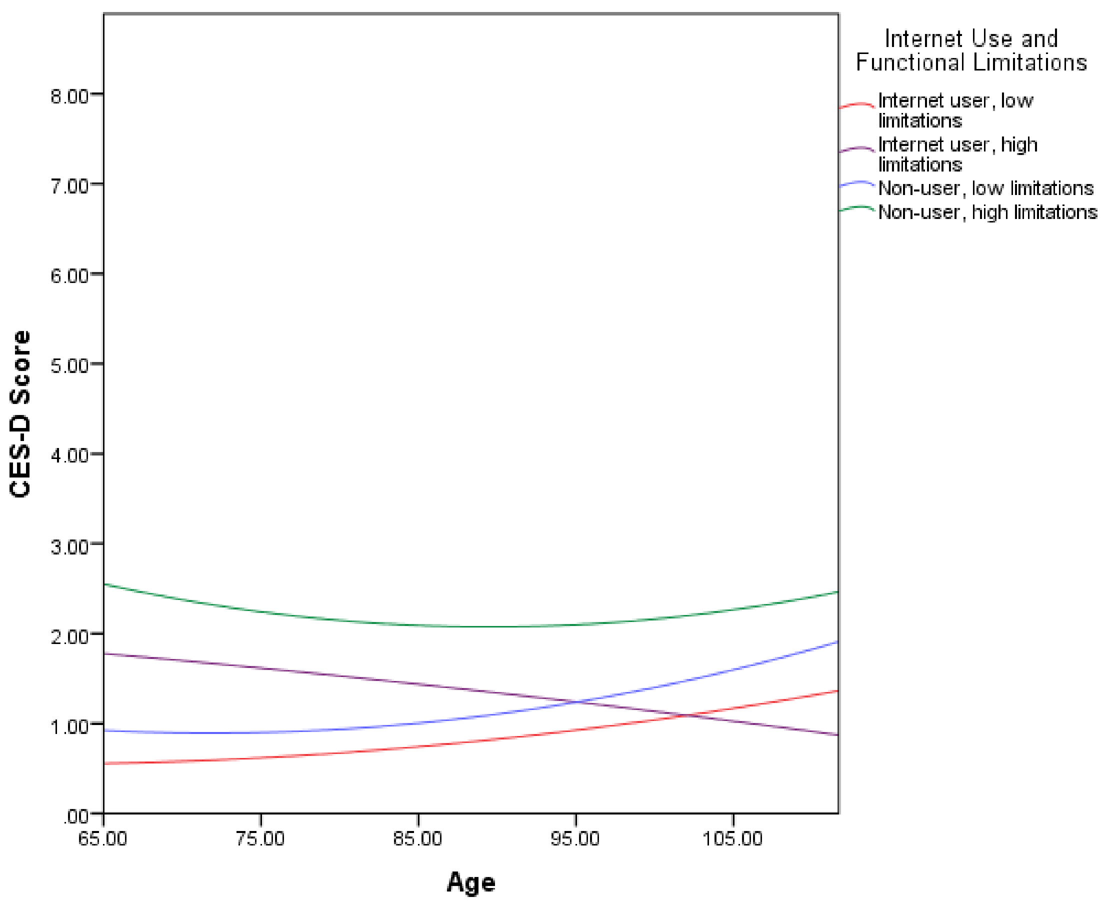

Figure 4.7: Internet Use and Functional Limitations Predicting CES-D Scores

functional limitations. Those with high limitations and report not using the Internet characteristically have the highest CES-D scores across all time points; interestingly, however, those with high limitations that report being an Internet user actually show *decreases* in CES-D scores over time. By the time these respondents reach their late-90's, their CES-D scores appear to equal those who report low functional limitations. In this way, Internet use can be viewed as a sort of *equalizer* with regards to depressive symptoms and functional limitations in that, over time, Internet use can contribute to more favorable CES-D scores in those with high limitations and make them *more equal* to those with low limitations. The final model, Model T, includes three-way interactions with *INTERNET*, *FUNCTION*, and the time variables, although these interactions were not found to be significant and their inclusion decreased model fit according to the increase in AIC and BIC statistics.

Mediation Testing

Up to this point Internet use and a variety of demographic variables have been found to significantly predict depressive symptomatology, although the results are mixed with regards to predicting change over time; with regards to Internet use, it does not appear that using the Internet significantly changes the trajectory of CES-D scores over time, although Internet users appear to report lower depression scores across all ages. The final analysis wherein depressive symptomatology is the outcome focuses on examining the effects of social integration and social support and whether these variables mediate the relationship between Internet use and CES-D.

Prior to mediation testing, growth curve models are estimated for all social integration and social support measures, the results of which are presented in Table 4.7 and 4.8. Model U in Table 4.7 examines the main effect of *SOCCOMP* (i.e., composition of social network) on depressive symptomatology. Neither time variable was found to be significant, similar to the findings when demographic predictors were included. Both *INTERNET* and *SOCCOMP* are significant predictors of CES-D scores. As in other models, Internet users tend to report lower CES-D scores compared to non-users (-0.4356, p<.001). In addition, those with a higher network composition score (i.e., those with more social relationships) report lower CES-D scores (-0.3873, p<.001). There are noticeably lower goodness-of-fit scores in Model U compared to earlier models, suggesting that the inclusion of SOCCOMP greatly increased model fit. While this model does not *directly* test for mediation, it should be noted that inclusion of the *SOCCOMP* variable does not drastically reduce the effect of *INTERNET* – in fact, comparing the *INTERNET* coefficient with the one presented in Model E of Table 4.2, the coefficient actually *increases*, suggesting that there is no significant mediation effect. This notion will be more formally tested later in this chapter. Model V includes interactions between *SOCCOMP* and both time variables, although these interactions were not found to be significant, suggesting that composition of social network is not a significant predictor of CES-D scores over time (i.e., the gap in CES-D scores neither increases nor decreases based on network composition).

Model W examines the main effects of close relationships on CES-D scores, including close relationships with a spouse (*CLOSESPOUSE*), children (*CLOSECHILD*), other family members (*CLOSEFAM*), and friends (*CLOSEFRIEND*). Having a close

Table 4.7: Fitting Change Trajectories with Network Composition and Close Relationships to CES-D Scores

		Model U *Main effect of Network Composition*	Model V *Network Composition predicting growth*	Model W *Main effect of Close Relationships*	Model X *Close relationships predicting growth*
Fixed Effects	Intercept	2.7687***	2.9056***	2.0035***	2.0031***
	AGE75	0.0043	-0.0162	0.0061	-0.0095
	AGE75^2	0.0002	-0.0013	-0.0001	0.0008
	INTERNET	-0.4356***	-0.4330***	-0.4095***	-0.4067***
	SOCCOMP	-0.3873***	-0.4300***		
	SOCCOMP x *AGE75*		0.0059		
	SOCCOMP x *AGE75*^{2}		0.0006		
	CLOSESPOUSE			-0.2480	-0.2603***
	CLOSESPOUSE x *AGE75*				0.0039
	CLOSESPOUSE x *AGE75*^{2}				0.0001
	CLOSECHILD			-0.0042	-0.0025
	CLOSECHILD x *AGE75*				-0.0009
	CLOSECHILD x *AGE75*^{2}				0.0000
	CLOSEFAM			-0.0012	-0.0037
	CLOSEFAM x *AGE75*				0.0001
	CLOSEFAM x				0.0001

	AGE75^2				
	CLOSEFRIEND			-0.0374***	-0.0322***
	CLOSEFRIEND x *AGE75*				0.0028**
	CLOSEFRIEND x *AGE75*^{2}				-0.0003*
Variance Components					
Level 1:	Within-person	1.4720***	1.4721***	1.4493***	1.4499***
Level 2:	In initial status	1.6031***	1.6057***	1.5740***	1.5740***
	In rate of change	0.0007	0.0006	0.0005	0.0003
	Covariance	0.0045	0.0051	0.0075	0.0085*
Goodness-of-fit					
	Deviance	46443.5	46433.4	47533.2	47518.7
	AIC	46461.5	46455.4	47557.2	47558.7
	BIC	46528.1	46536.8	47646.3	47707.3

*$p<.05$; **$p<.01$; ***$p<.001$
$N = 9414$

relationship with a spouse and having close relationships with friends was significantly associated with lower CES-D scores (p<.001). Close relationships with children and close relationships with other family members were not significant predictors of depressive symptomatology. Even accounting for these variables, *INTERNET* retained a significant relationship with depressive symptomatology such that Internet users reported lower CES-D scores (p<.001), indicating that the additional *CLOSE* variables may not be serving as significant mediators. Model X includes interactions between the *CLOSE* variables and both time variables. Neither *AGE75* nor $AGE75^2$ were found to have significant interactions with the *CLOSE* variables except in the case of close relationships with friends: the coefficient for interaction with the linear term (0.0028, p<.01) indicates that over time the gap in CES-D scores increases based on the number of close relationships with friends (i.e., the slope of CES-D scores is steeper for those with few or no close relationships with friends), and the coefficient for the interaction with the quadratic term (-0.0003, p<.05) indicates that the growth in this gap decreased over time.

Model Y in Table 4.8 examines the main effects of frequency of contact with social network on CES-D scores in the absence of interactions with time. Frequency of contact with children (-0.0542, p<.001) and friends (-0.1132, p<.001) were found to be significant predictors of CES-D scores such that increased contact was associated with decreased depressive symptomatology. No significant relationship was found between contact with other family members and CES-D scores. Even accounting for these measures *INTERNET* retained a significant relationship with CES-D scores (-0.3877, p<.001) such that Internet users, compared to non-users, on average reported lower scores. This hints at the notion that while contact with social networks may affect CES-D scores, these measures may not be mediating the effect of Internet use. Model Z adds in interactions between the contact measures and the time variables. These interactions were not found to be significant save for one: contact with family was found to have a significant interaction with the linear term, indicating that the gap in CES-D scores decreased over time based on contact with family members other than children. This finding is somewhat surprising given that contact with family was not found to have a significant main effect on CES-D scores. This implies that while the *gap itself* in CES-D scores among those with higher contact scores and those with lower contact scores is small and non-significant, the *gap does close at a significant rate* (-0.0064, $p<.05$).

Model AA in Table 4.8 examines measures of social support as predictors of depressive symptomatology in the absence of interactions with *AGE75* and $AGE75^2$. Overall, all measures of social support were found to be significant predictors of CES-D scores such that higher (i.e., better) social support scores were associated with lower CES-D scores. The largest coefficients were found for social support from spouses (-0.2602, $p<.001$) and children (-0.1162, $p<.001$). As with the social integration measures in Table 4.7 and Table 4.8, even accounting for social support the Internet use measure retained a significant relationship with CES-D scores; on average, Internet users enjoyed more favorable CES-D scores (-0.4061, $p<.001$). While mediation testing must be done to confirm, it appears that social support does not mediate the relationship between Internet use and depressive symptomatology, although all social support measures do appear to significantly predict CES-D scores. Model AB adds in interactions between the social support measures and the time variables, however none of these interactions were found to be significant predictors of CES-D scores.

Table 4.8: Fitting Change Trajectories with Contact Frequency and Social Support to CES-D Scores

		Model Y *Main effect of Contact Frequency*	Model Z *Contact frequency predicting growth*	Model AA *Main effect of social support*	Model AB *Social support predicting growth*
Fixed Effects	Intercept	1.8127***	1.7796***	2.3388***	2.3504***
	AGE75	0.0136***	0.0168	0.0055	-0.0033
	AGE75^2	0.0003	0.0008	0.0000	0.0003
	INTERNET	-0.3877***	-0.3901***	-0.4061***	-0.4022***
	CONTCHILD	-0.0542***	-0.0542**		
	CONTCHILD x *AGE75*		0.0008		
	CONTCHILD x *AGE75*^{2}		-0.0001		
	CONTFAM	0.0202	0.0239		
	CONTFAM x *AGE75*		-0.0064*		
	CONTFAM x *AGE75*^{2}		0.0003		
	CONTFRIEND	-0.1132***	-0.1019***		
	CONTFRIEND x *AGE75*		0.0035		
	CONTFRIEND x *AGE75*^{2}		-0.0004		
	SUPSPOUSE			-0.2602***	-0.2759***
	SUPSPOUSE x *AGE75*				0.0045
	SUPSPOUSE x				0.0001

	AGE75^2				
	SUPCHILD			-0.1162***	-0.1246***
	SUPCHILD x *AGE75*				0.0004
	SUPCHILD x *AGE75*^{2}				0.0002
	SUPFAM			-0.0428*	-0.0410*
	SUPFAM x *AGE75*				-0.0047
	SUPFAM x *AGE75*^{2}				0.0002
	SUPFRIEND			-0.0749***	-0.0620**
	SUPFRIEND x *AGE75*				0.0046
	SUPFRIEND x *AGE75*^{2}				-0.0005
Var. Comp.					
Level 1:	Within-person	1.4995***	1.5000***	1.4410***	1.4406***
Level 2:	In initial status	1.6925***	1.6869***	1.5662***	1.5660***
	In rate of change	0.0000	0.0000	0.0006	0.0005
	Covariance	0.0059	0.0058	0.0062	0.0064
Goodness-of-fit					
	Deviance	49799.0	49791.7	48071.9	48060.2
	AIC	49821.0	49825.7	48095.9	48100.2
	BIC	49903.1	49952.6	48185.2	48249.0

*p<.05; **p<.01; ***p<.001

N = 9414

While the growth curve models previously presented suggest that there is little to no mediation effect of social integration/social support on the relationship between Internet use and depressive symptomatology, mediation testing is conducted to asses this notion as outlined by Bauer et al. (2006). As discussed in the previous chapter, this method simultaneously estimates the indirect effect of Internet use on CES-D scores (i.e., how Internet use affects the mediators which in turn affect the outcome) and total effect of Internet use on CES-D scores to determine if significant mediation is occurring. A significant result for the indirect effect indicates that mediation is occurring. Should both the indirect effect *and* the total effect be significant, then partial mediation is occurring and there remains a direct effect of Internet use on the outcome. An advantage of this method is that, unlike other mediation analysis techniques, the Bauer et al. method is designed for multilevel data and can thus be used in longitudinal analysis. Table 4.9 contains the average indirect and total effects of Internet use on CES-D scores by mediator as well as standard errors and 95% confidence intervals.

Because the mediation analysis incorporates a methodology that is somewhat different from the individual growth curve analysis (i.e., the outcome is not depression alone, but a stacked version of depression and the mediators), the coefficients are not immediately comparable which explains why in most instances the total effects of Internet use on CES-D scores do not match the coefficients presented earlier. For the purposes of interpreting the mediation effects, the coefficients will be ignored and focus will be placed only on the significance of the coefficients. Evidence for mediation is found for the following variables: composition of social network, frequency of contact with children, frequency of contact with other family, frequency of contact with friends, social

Table 4.9: Indirect and Total Effects of Internet Use on CES-D Scores

	Average	*Standard Error*	*Lower Confidence Limit*	*Upper Confidence Limit*
SOCCOMP				
Indirect Effect	0.1301***	0.0173	0.0962	0.1641
Total Effect	0.3306***	0.0317	0.2686	0.3927
CLOSESPOUSE				
Indirect Effect	-0.0098	0.0056	-0.0012	0.0012
Total Effect	-0.1076**	0.0382	-0.1825	-0.0326
CLOSECHILD				
Indirect Effect	-0.0470	0.0653	-0.1750	0.0810
Total Effect	-0.4166***	0.0898	-0.5927	-0.2406
CLOSEFAM				
Indirect Effect	-0.0840	0.0905	-0.2613	0.0933
Total Effect	0.3663**	0.1149	0.1411	0.5916
CLOSEFRIEND				
Indirect Effect	0.0165	0.0502	-0.0819	0.1149
Total Effect	0.5234***	0.0602	0.4055	0.6413
CONTCHILD				
Indirect Effect	0.1700***	0.0196	0.1316	0.2083
Total Effect	0.2500***	0.0305	0.1901	0.3098
CONTFAM				
Indirect Effect	0.0668***	0.0182	0.0312	0.1023
Total Effect	0.7184***	0.0305	0.6586	0.7781
CONTFRIEND				
Indirect Effect	-0.3039***	0.0752	-0.4513	-0.1565
Total Effect	0.7731***	0.2133	0.3551	1.1912
SUPSPOUSE				
Indirect Effect	0.0046	0.0100	-0.0151	0.0243
Total Effect	0.0132	0.0200	-0.0261	0.0524
SUPCHILD				
Indirect Effect	0.0022	0.0188	-0.0347	0.0392
Total Effect	-0.0976***	0.0275	-0.1514	-0.0437
SUPFAM				
Indirect Effect	-0.0237***	0.0039	-0.0314	-0.0159
Total Effect	0.1077***	0.0204	0.0678	0.1477
SUPFRIEND				
Indirect Effect	0.0621***	0.0017	0.0588	0.0654
Total Effect	0.1837***	0.0174	0.1496	0.2178

Confidence limits reflect 95% confidence intervals

N = 9414

support of other family, and social support for friends. The magnitude of the indirect effects for network composition and contact with children, when compared to the direct effects, indicates that these variables may be the strongest mediators of the social integration and social support measures. For each variable the total effect was also found to be significant, suggesting that Internet use has an association with CES-D scores independent of the mediators. Support is found for the mediation hypotheses suggesting that social integration and social support mediate the relationship between Internet use and depressive symptomatology but that Internet use also has an effect independent of these measures.

In summary, Internet use is found to be a significant predictor of depressive symptomatology, although there is no evidence to support the notion that Internet use affects change over time. On average, Internet users compared to non-users reported lower CES-D scores. The relationship between Internet use and CES-D scores was significantly moderated by demographic measures, such as income, employment status, self-rated health, and functional limitations. Social integration and social support measures were also found to be significant predictors of depressive symptomatology, however mediation analysis suggests that these measures only partially mediate the relationship between Internet use and depressive symptomatology and not across all potential mediators.

CHAPTER FIVE

LIFE SATISFACTION

According to the *hedonic treadmill* theory presented by Brickman and Campbell (1971), individual levels of life satisfaction do not change significantly over time. This is because positive and negative changes to an individual's overall status only have temporary effects, as the individual is ultimately able to adjust to these changes and bring their satisfaction level back to baseline. However, with regards to aging populations, some empirical research has found that this is not the case in later life, as studies have shown life satisfaction to move in a negative direction (i.e., decrease) over time (for example, see Mroczek and Spiro 2005), particularly towards end-of-life (Gerstorf et al. 2008). Characteristics of social life, such as social engagement and quality of social ties, have been shown to significantly affect life satisfaction (Berg et al. 2006; Darbonne et al. 2012; Jang et al. 2004). The focus of this chapter is to examine whether Internet use serves as a significant predictor of life satisfaction in older adults and to determine if measures of social integration and social support act as significant moderators in this relationship.

It is important to note the methodological differences between the analysis presented in this chapter and the analysis presented in the previous chapter, wherein depressive symptomatology was the primary outcome. Previously, individual growth curve modeling was used to measure Internet use, social integration/support, and depression and how they changed over time. Due to the way in which life satisfaction is measured in the HRS (for review, see Chapter 3), there are no HRS respondents that have 3 available time points of life satisfaction data. While growth curve modeling is possible with less than three time points, it is not recommended (Singer and Willett 2003) as the procedure would only be able to estimate a linear growth in life satisfaction; in this case, the procedure is not necessarily any stronger than simpler methods such as OLS regression. As such, for the life satisfaction outcome, the analysis carries out mediation testing using the methods presented by Baron and Kenny (1986) and using OLS regression. Data for the analysis come primarily from the 2012 wave of the HRS. In addition, measurement of the outcome at the 2008 wave is used in the analysis as a control variable in the final model.

Mediation Testing

According to Baron and Kenny (1986), the first step to mediation testing is to determine if a significant relationship exists between the primary predictor (i.e., Internet use) and the mediators (i.e., social integration and social support measures). OLS regressions were run wherein Internet use is the predictor and each social integration/social support measure is the outcome. Results are presented in Table 5.1. Internet use was found to be a significant predictor of composition of social network, close relationships with spouse, close relationships with children, close relationships with family, close relationships with friends, contact with children, contact with family, contact with friends, social support from spouse, social support from family, and social support from friends. Of all mediators, Internet use was not a significant predictor of social support from children (because of this, this variable is dropped from all other regression models). Interestingly, the direction of each significant relationship was not consistent. Internet use was found to have a positive relationship with composition of social network, close relationships with spouses and friends, all contact variables, and social support of spouse and friends; conversely, Internet use had a negative relationship with close relationships with children and other family as well as social support from children and family.

Table 5.1: Internet Use as a Predictor of Social Integration/Support (OLS Regression, HRS 2012)

Mediator	Relationship with Internet Use
SOCCOMP	0.238*** (0.029)
CLOSESPOUSE	0.417*** (0.052)
CLOSECHILD	-0.358*** (0.070)
CLOSEFAM	-0.496*** (0.109)
CLOSEFRIEND	0.317** (0.113)
CONTCHILD	0.620*** (0.043)
CONTFAM	0.281*** (0.043)
CONTFRIEND	0.885*** (0.042)
SUPSPOUSE	0.447*** (0.050)
SUPCHILD	-0.052 (0.033)
SUPFAM	-0.168*** (0.036)
SUPFRIEND	0.112** (0.033)

OLS coefficients (with standard deviations) presented ; *p<.05; **p<.01; ***p<.001

According to Baron and Kenny (1986), the next step to mediation testing is to evaluate the relationship of the primary predictor (i.e., Internet use) and the primary outcome (i.e., life satisfaction). Model A in Table 5.2 contains the results of this regression and shows that, in the absence of any control variables, Internet use is a significant predictor of life satisfaction. Overall, Internet users score approximately 0.139 points higher in life satisfaction (on a scale of 0-4, with 4 = higher life satisfaction) compared to non-users (*p*<.001). As with depressive symptoms in Chapter 4, it initially appears that Internet users enjoy better outcomes than non-users.

Table 5.2: Internet Use and Social Integration/Support Predicting Life Satisfaction (OLS Regression, HRS 2012)

Predictor	Model A *INTERNET*	Model B *INTERNET and Social Integration*	Model C *INTERNET and Social Support*	Model D *Full model*
INTERNET	0.139***	0.039	0.076*	0.045
	(0.033)	(0.036)	(0.033)	(0.037)
SOCCOMP		-0.054		-0.098**
		(0.035)		(0.036)
CLOSESPOUSE		0.136***		0.046
		(0.017)		(0.032)
CLOSECHILD		0.034**		0.034**
		(0.010)		(0.010)
CLOSEFAM		0.001		-0.002
		(0.007)		(0.007)
CLOSEFRIEND		0.011		0.009
		(0.006)		(0.006)
CONTCHILD		-0.003		0.008
		(0.016)		(0.016)
CONTFAM		0.010		-0.026
		(0.016)		(0.019)
CONTFRIEND		0.063***		0.063***
		(0.016)		(0.018)
SUPSPOUSE			0.131***	0.117***
			(0.012)	(0.033)
SUPFAM			0.054**	0.079***
			(0.017)	(0.022)
SUPFRIEND			0.056**	0.013
			(0.019)	(0.023)
Adjusted R^2	0.007	0.060	0.058	0.069

OLS coefficients (with standard deviations) presented; *p<.05; **p<.01; ***p<.001
N = 2494

Model B in Table 5.2 incorporates all the social integration mediators into the analysis, including composition of social network, the close relationships variables, and the contact variables. Of the mediators, close relationships with spouse, close relationships with children, and contact with friends were found to significantly predict life satisfaction such that closer relationships and increased frequency of contact was associated with increased life satisfaction. Inclusion of the social integration measures explained away the effect of Internet use on life satisfaction, as *INTERNET* was not found to have a significant relationship in Model B. As seen in Table 5.2, the coefficient for Internet use dropped a full tenth of a point between Model A and Model B, indicating that inclusion of the social integration measures accounted for approximately 72% of the effect of *INTERNET* on life satisfaction. In this way, support is found for the notion that social integration acts as a strong and significant mediator.

Model C examines *INTERNET* as a predictor of life satisfaction along with the social support variables (the social integration measures are taken out for this regression). Unlike the previous model, *INTERNET* retains a significant relationship with life satisfaction when accounting for social support (p<.05). Overall Internet users, compared to non-users, score 0.076 points higher in life satisfaction. Social support accounts for approximately 45% of the effect of Internet use on the outcome. All three included social support measures were found to be significantly associated with life satisfaction such that increased support from a spouse, from family, and from friends were all associated with higher life satisfaction scores.

Model D in Table 5.2 incorporates both social integration and social support simultaneously to predict life satisfaction. Close relationships with children, increased frequency of contact with friends, social support from spouse, and social support from family were all positively associated with life satisfaction. Composition of social network, interestingly, was negatively associated with life satisfaction. In this model, no significant relationship was found between Internet use and life satisfaction. Results from Table 5.2 indicate that social integration and social support both mediate the relationship between Internet use and life satisfaction; social integration is found to mediate this relationship to a very large degree, as Internet use retains no significant relationship with the outcome when social integration measures are included.

Including Demographic Measures

While the findings presented in Tables 5.1 and 5.2 are enough to conclude that social integration and social support mediate the relationship between Internet use and life satisfaction, an additional model was run to determine if inclusion of demographic characteristics explained away the previously found relationships. The results are presented in Table 5.3. Note that the sample size is smaller than the previous models; this is due to missing values for some of the demographic measures. Added measures include age, sex, education, race, income, employment status, self-rated health, functional limitations, and a measure of overall life satisfaction in 2008. In the final model, close relationships with children, increased social support from spouses and family, better health, and increased life satisfaction were all associated with elevated levels of life satisfaction in 2008. Composition of social network was associated with decreased life satisfaction in 2012. Notably, the coefficient for Internet use has been reduced to almost 0 in the final model. Thus social integration, social support, and other demographic

Table 5.3: Full OLS Regression Model Predicting Life Satisfaction (HRS 2012)

Predictor	Relationship with Life Satisfaction
INTERNET	0.004
	(0.037)
SOCCOMP	-0.089**
	(0.033)
CLOSESPOUSE	0.018
	(0.029)
CLOSECHILD	0.025**
	(0.009)
CLOSEFAM	0.000
	(0.006)
CLOSEFRIEND	0.004
	(0.006)
CONTCHILD	0.002
	(0.015)
CONTFAM	-0.015
	(0.018)
CONTFRIEND	0.027
	(0.017)
SUPSPOUSE	0.097**
	(0.030)
SUPFAM	0.054**
	(0.020)
SUPFRIEND	-0.001
	(0.021)
AGE	0.004
	(0.003)
SEX	0.010
	(0.033)

EDUCATION	-0.002
	(0.007)
RACE	0.040
	(0.045)
INCOME	-0.004
	(0.006)
EMPLOY	0.055
	(0.043)
HEALTH	0.176***
	(0.017)
FUNCTION	-0.027
	(0.034)
LIFESATISFY08	0.328***
	(0.020)
Adjusted R^2	0.238

OLS coefficients (with standard deviations) presented; *p<.05; **p<.01; ***p<.001
N = 2442

characteristics almost explain away the entire effect of Internet use on life satisfaction in older adults.

One final note regarding the life satisfaction analysis: in examining the model fit statistic (adjusted R^2), we see that Internet use, social integration, and social support overall do not explain much of the variation in life satisfaction scores among HRS respondents (i.e., higher scores indicate increased variation explained or "better model fit"). Inclusion of the demographic characteristics, however, increased the statistic to 0.238, indicating that the full model explained nearly 24% of the variation in life satisfaction scores among the sample. In this way demographic measures, particularly self-rated health and previous levels of life satisfaction, may be better indicators of current life satisfaction than Internet use or the mediators.

CHAPTER SIX

LONELINESS

While the stereotype that loneliness is common among older adults has come into question (for example, see Dykstra 2009), empirical evidence finds support for the notion that older adults are at risk for increased loneliness due to changes that occur in late life, such as the death of a spouse or partner (for example, see Dykstra, van Tilburg, and Gierveld 2005). Other factors associated with increased loneliness in old age include lower education, lower income, poor health and increased disability, increased stress, lack of social contacts or dissatisfaction with said contacts, and certain types of living arrangements (Hawkley et al. 2008; Routasalo et al. 2006; Russell 2009; Savikko et al. 2005; Victor et al. 2005). This study seeks to add to previous literature and determine if Internet use serves as a significant predictor of loneliness in older adults using individual growth curve modeling. This study also seeks to add to the literature by determining if social integration and social support act as mediators in this relationship.

Growth Curve Analysis

As with the analyses wherein depressive symptomatology was the primary outcome, the growth curve analyses of loneliness begins with the unconditional means model which estimates the grand mean of loneliness scores across all individuals in the absence of time and other predictors. The unconditional means model also allows for the partitioning of outcome variation that can assist in determining what types of predictors should be added to the model. Model A in Table 6.1 includes the results of fitting the unconditional means model using the HRS data. The intercept for this model is 0.4650 (p<.001), indicating that, on average, HRS respondents across all measurement occasions reported relatively low loneliness scores (scaled 0-2, with 2 = high level of loneliness). Both the within variance component (0.1209) and the level-2 variance component associated with initial status (0.1531) were significant at the p<.001 level, suggesting that both level-1 and level-2 predictors can be added to the model for better fit. These variance components also allow for the calculation of the ICC, which comes out to be approximately 0.5588. This value suggests that about 56% of the total variation in loneliness scores is the result of interindividual differences; because this value is larger than the threshold of 25% (Heinrich and Lynn 2001; Kreft 1996), growth curve modeling can be deemed an appropriate technique for modeling loneliness with the HRS data.

Model B in Table 6.1 shows the results of fitting the unconditional growth model which adds the time variable as a predictor of loneliness. Like the depressive symptoms analyses, the time variable used is age centered at 75 (*AGE75*). While centering time in this way changes the interpretation of the intercept, it prevents issues associated with multicollinearity when higher-order polynomials are added (as will be in Models C and D). The intercept for Model B is 0.4491 (p<.001), smaller than the grand mean found in Model A. This value can be interpreted as the average loneliness score for HRS respondents aged 75. The linear time term *AGE75* was found to be a significant predictor of loneliness at the p<.001 level; on average, an individual's loneliness score will increase by approximately 0.0059 points each year. While *AGE75* was found to be a

Table 6.1: Fitting Alternative Polynomial Change Trajectories to Loneliness Scores

		Model A *No change*	Model B *Linear change*	Model C *Quadratic change*	Model D *Cubic change*
Fixed Effects	Intercept	0.4650***	0.4491***	0.4449***	0.4492***
	AGE75 (linear term)		0.0059***	0.0048***	0.0041***
	$AGE75^2$ (quadratic term)			0.0001	-0.0000
	$AGE75^3$ (cubic term)				0.0000
Variance Components					
Level 1:	Within-person	0.1209***	0.1190***	0.1190***	0.1189***
Level 2:	In initial status	0.1531***	0.1498***	0.1497***	0.1496***
	In rate of change		0.0001	0.0001	0.0001*
	Covariance		-0.0004	-0.0004	-0.0004
Goodness-of-fit					
	Deviance	18120.3	18054.4	18051.4	18049.0
	AIC	18126.3	18066.4	18065.4	18065.0
	BIC	18148.8	18111.3	18117.8	18125.0

*p<.05; **p<.01; ***p<.001
N = 9414

significant predictor, the magnitude of estimated change over time is small, much like what was found in the depressive symptoms analyses. The within-variance component and level-2 component associated with initial status suggest that including time-variant and time-invariant predictors may improve model fit. However, the level-2 component associated with rate of change (0.0001) was not found to be significant at least at the p<.05 level and suggests that inclusion of time-invariant predictors may not improve predictions in rate of change. In addition, the covariance component (-0.0004) was not

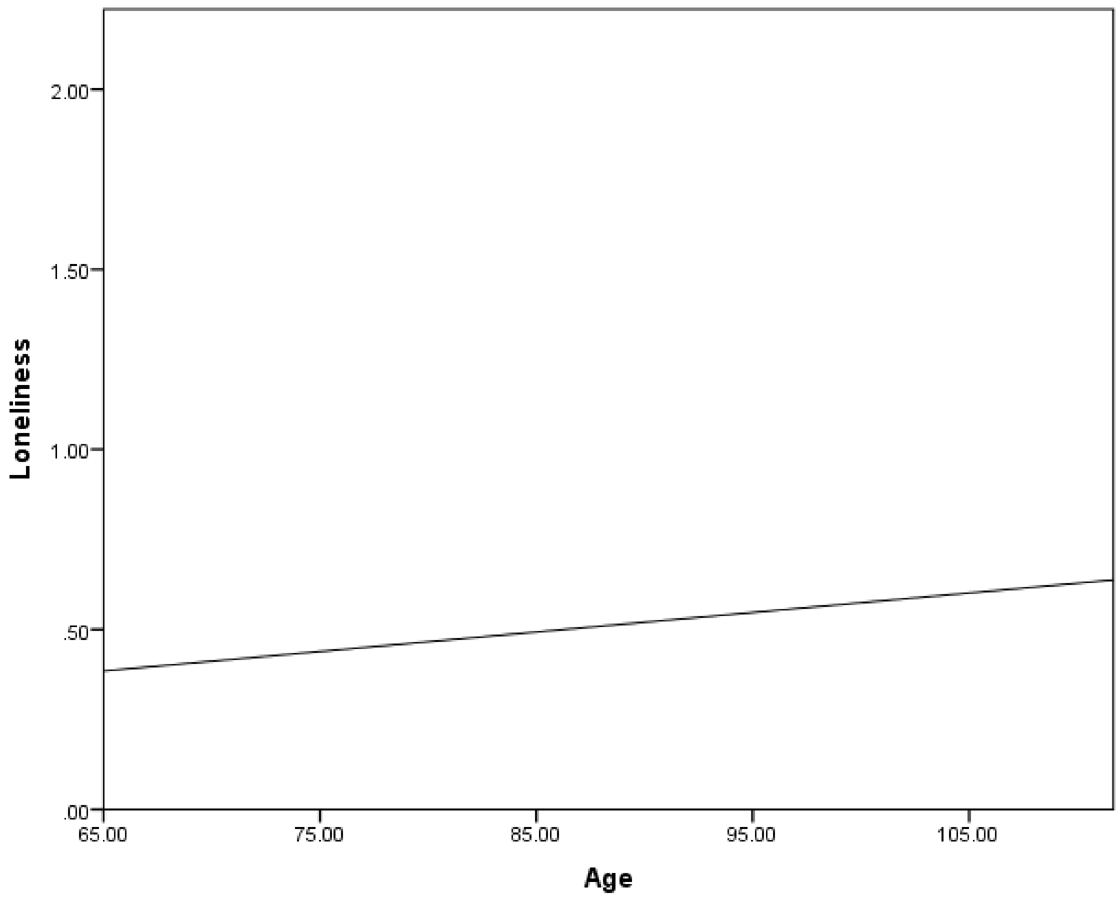

Figure 6.1: Fitted Line of Loneliness Scores by Age

found to be significant, suggesting that those with high loneliness scores at baseline (i.e., age 75) were not significantly different from those with low scores in regards to rates of change in loneliness. Finally, decreases in all three goodness-of-fit values between Models A and B suggests that including *AGE75* improved overall model fit.

Model C adds the quadratic term $AGE75^2$ to the growth curve model but is not found to be significant at least at the p<.05 level, suggesting that the rate of growth in loneliness over time does not significantly increase or decrease and that the trajectory of loneliness in old age may be linear. An increase in the BIC statistic between Models B and C also provides evidence that adding the quadratic term to the model does not increase model fit. Model D incorporates the cubic term $AGE75^3$ and is also not found to be significant at least at the p<.05 level; in addition, the BIC statistic increases once again. The results of these models provide evidence supporting the notion that within the HRS data loneliness grows in a linear fashion. This fitted line is presented in Figure 6.1. Support is found for Hypothesis 1 which suggests that loneliness increases as an individual ages. Because neither the quadratic term nor the cubic term were found to be significant predictors of loneliness, both are dropped from future models.

Predictors are added to the growth curve analyses to determine what factors affect loneliness in old age and if these factors have a significant impact over time. Table 6.2 shows the results of these models and begins with the addition of Internet use (*INTERNET*) as a predictor of loneliness in Model E. *INTERNET* is first examined without an interaction with *AGE75* to determine the main effect of Internet use (i.e., the effect of Internet use on initial status). The coefficient for *INTERNET* (-0.1121, p<.001) suggests that Internet users, compared to non-users, report lower levels of loneliness. The goodness-of-fit statistics, which decreased between Model D in Table 6.1 and Model E in Table 6.2, indicate that the addition of *INTERNET* as a predictor improved model fit. Support is found for Hypothesis 2, with Internet use significantly predicting loneliness. Model F adds an interaction between *INTERNET* and *AGE75* to determine if Internet use acts as a predictor of loneliness over time. The coefficient for this interaction (-0.0008) suggests that the gap in loneliness scores between Internet users and non-users decreases over time; however, the interaction is not found to be significant at least at the p<.05

Table 6.2: Fitting Change Trajectories with Internet Use to Loneliness Scores

		Model E *Main effect of INTERNET*	Model F *INTERNET predicting growth*	Model G *Main effect of demographic predictors*	Model H *Growth and demographic predictors*
Fixed Effects	Intercept	0.4851***	0.4845***	0.6829***	0.6778***
	AGE75	0.0047***	0.0049***	0.0019*	0.0051
	INTERNET	-0.1121***	-0.1110***	-0.0335**	-0.0333**
	INTERNET x *AGE75*		-0.0008		
	SEX			0.0399***	0.0414***
	SEX x *AGE75*				-0.0002
	EDUCATION			-0.0064**	-0.0062**
	EDUCATION x *AGE75*				-0.0001
	RACE			-0.0141	-0.0162
	RACE x *AGE75*				0.0011
	INCOME			-0.0169***	-0.0171***
	INCOME x *AGE75*				0.0003
	EMPLOY			0.0365*	0.0363*
	EMPLOY x *AGE75*				-0.0023
	HEALTH			-0.0707***	-0.0704***
	HEALTH x *AGE75*				0.0001
	FUNCTION			0.0871***	0.0943***
	FUNCTION x *AGE75*				-0.0041*

Variance Components					
Level 1:	Within-person	0.1194***	0.1193***	0.1222***	0.1224***
Level 2:	In initial status	0.1456***	0.1456***	0.1219***	0.1216***
	In rate of change	0.0001	0.0001	0.0001*	0.0001
	Covariance	-0.0003	-0.0003	-0.0000	0.0000
Goodness-of-fit					
	Deviance	17910.6	17910.4	14707.9	14699.0
	AIC	17924.6	17926.4	14735.9	14741.0
	BIC	17977.0	17986.3	14838.1	14894.3

*p<.05; **p<.01; ***p<.001

N = 9414

level. In this way, Internet use is not found to significantly predict the trajectory of loneliness over time. This is supported by the plot of loneliness trajectories in Figure 6.2 between Internet users and non-users, as the slope for growth in loneliness does not appear to be significantly different between the two groups. No evidence is found to support Hypothesis 3.

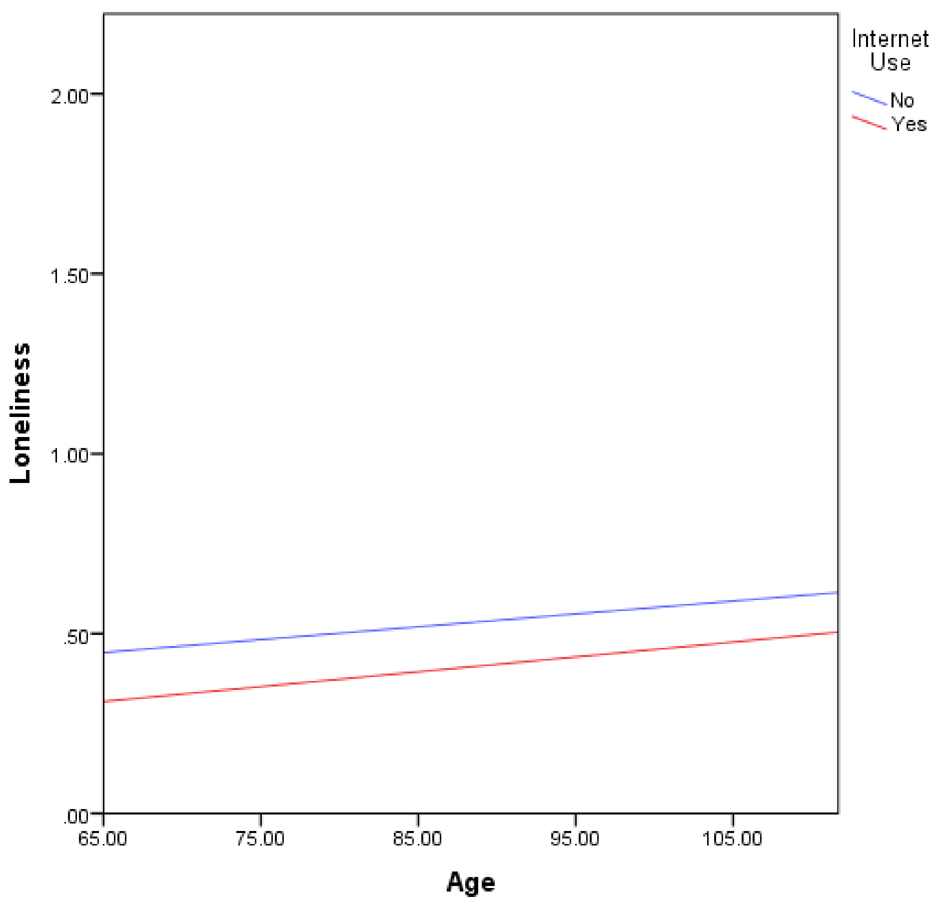

Figure 6.2: Difference in Loneliness Scores between Internet Users and Non-Users

Model G includes demographic variables without interactions with *AGE75*. Note that because no significant interaction between *INTERNET* and *AGE75* was found, the interaction was dropped for Model G and all future models. Overall, being female, being employed, and having a higher number of functional limitations were associated with increased scores in loneliness while being more educated, having increased income, and having better self-rated health were associated with decreased loneliness. Race was not found to be a significant predictor of loneliness scores. While *INTERNET* remained a significant predictor of loneliness in Model G, the inclusion of the demographic characteristics explained away much of the variable's effect, as the coefficient was reduced to -0.0335 (p<.01). The coefficient for *AGE75* also decreased substantially, indicating that, like with depressive symptoms, loneliness scores may be less dependent on age and more dependent on characteristics that change late in life. Model H adds interactions between the demographic variables and the linear term *AGE75*. The only interaction that was found to be significant was the interaction between functional limitations and time (-0.0041, p<.05). In summary, while HRS respondents with higher functional limitations on average reported higher loneliness scores, the gap in loneliness between those with high limitations and those with low limitations decreased over time. Even accounting for these interactions, *INTERNET* still significantly predicted loneliness (-0.0333, p<.01) such that Internet users reported lower loneliness.

Moderation Testing

Additional analyses were conducted to examine whether any of the demographic characteristics acted as moderators in the relationship between Internet use and loneliness. Sex, education, race, self-rated health, and functional limitations were not found to significantly moderate the relationship between *INTERNET* and loneliness.

Both *INCOME* and *EMPLOY*, however, were found to be significant moderators. These interactions are presented in Table 6.3 and Table 6.4 as well as Figure 6.3 and 6.4.

Table 6.3: Interactions between *INTERNET* and *INCOME* Predicting Loneliness Scores

		Model I *INTERNET and INCOME*	Model J *Main Effects of INTERNET and INCOME Interaction*	Model K *Interaction of INTERNET and INCOME Over Time*
Fixed Effects	Intercept	0.5587***	0.5725***	0.5741***
	AGE75	0.0030***	0.0030***	0.0026**
	INTERNET	-0.0726***	-0.1248***	-0.1277***
	INCOME	-0.0240***	-0.0287***	-0.0288***
	INTERNET x *INCOME*		0.0123**	0.0129***
	INTERNET x *INCOME* x *AGE75*			0.0004
Variance Components				
Level 1:	Within-person	0.1220***	0.1221***	
Level 2:	In initial status	0.1373***	0.1368***	
	In rate of change	0.0001	0.0001	
	Covariance	-0.0000	-0.0000	
Goodness-of-fit				
	Deviance	15250.1	15238.3	15236.6
	AIC	15266.1	15256.3	15256.6
	BIC	15324.6	15322.1	15329.6

*p<.05; **p<.01; ***p<.001
N = 9414

Model I in Table 6.3 presents a simplified growth model wherein the only predictors of loneliness that are included are *AGE75*, *INTERNET*, and *INCOME*. Taking out other potentially significant predictors allows a clearer look at the relationships between Internet use, income, and time and their interactions. As shown in Model I, all three included predictors are found to be significant predictors of loneliness: on average, loneliness scores increase with age (0.0030, $p<.001$), Internet users have lower loneliness scores compared to non-users (-0.0726, $p<.001$), and loneliness scores are lower for those with increased income (-0.0240, $p<.001$). Model J includes an interaction between *INTERNET* and *INCOME* independent of time to determine if income acts as a moderator of initial status. Inclusion of this interaction changes the interpretation of other coefficients. *INTERNET* is now interpreted as the difference in loneliness scores between Internet users and non-users *among those in the lowest income bracket*. The coefficient (-0.1248, $p<.001$) indicates that among the poorest HRS respondents, Internet users report lower loneliness scores compared to non-users. *INCOME* is now interpreted as differences in loneliness scores between income brackets *among Internet non-users* and shows that loneliness is lower for those with higher income (-0.0287, $p<.001$). The interaction is found to be significant (0.0123, $p<.01$) and all goodness-of-fit statistics decrease, suggesting that *INCOME* moderates the effect of *INTERNET* on loneliness scores and that including this interaction in the model increases overall model fit.

Interpretation of the interaction is more clearly seen when examining the plot of loneliness scores between Internet users with low or high income and non-users with low or high income; this plot is presented in Figure 6.3. Overall, as with previous models loneliness scores increase over time for all groups. Internet non-users with low income

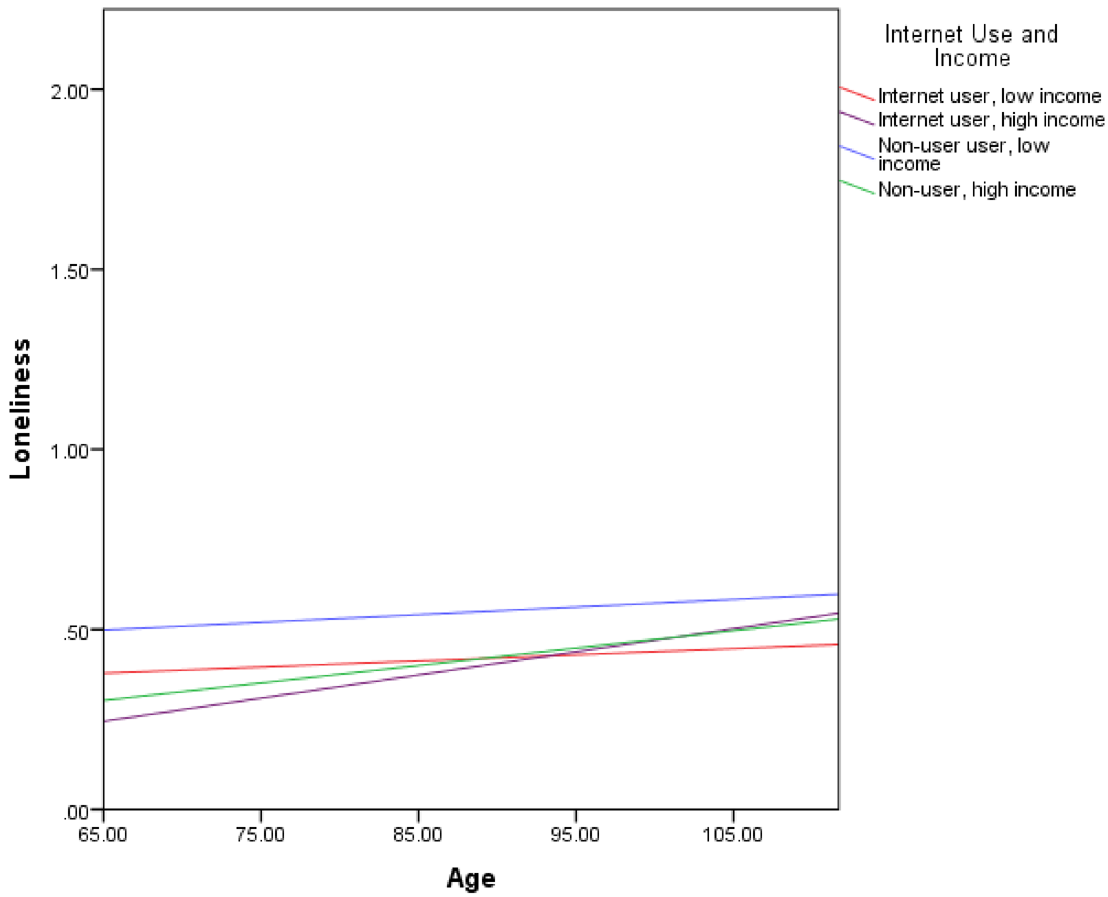

Figure 6.3: Internet Use and Income Predicting Loneliness Scores

report the highest loneliness scores across all age categories. Internet users and non-users with high income have very similar loneliness scores across age groups and also very similar growth trajectories, suggesting that Internet use may be less of a factor in predicting loneliness among the more wealthy HRS respondents. For Internet users reporting low income, at age 65 these respondents report the second-highest loneliness scores (second only to non-users with low income); however, for these respondents the growth in loneliness is less than all other groups such that by later life these respondents report the lowest loneliness scores. This suggests that, among those with more disadvantageous economic resources, Internet use may prevent more steep growth in loneliness over time.

Model K in Table 6.3 includes a three-way interaction between *INTERNET*, *INCOME*, and the linear time variable. Inclusion of these variables changed the coefficients of other variables only slightly and did not explain away any previously found significant results. In addition, the interaction itself was not found to be a significant predictor of loneliness and both the AIC and BIC statistics grew between models, suggesting that inclusion of this three-way interaction actually decreased model fit.

Table 6.4 presents results of examining the interaction between *INTERNET* and *EMPLOY*. The first model, Model L, presents a simplified model of *INTERNET* and *EMPLOY* predicting loneliness scores in the absence of other predictors (except time) and in the absence of any interactions. Model L shows that both Internet users report lower loneliness scores (-0.1113, p<.001) and those who are employed report lower loneliness scores (-0.0273, p<.05). Model M includes an interaction between *INTERNET* and *EMPLOY*. Inclusion of this interaction changes the interpretation of other coefficients. *INTERNET* is now interpreted as the difference in loneliness between Internet users and non-users *among the unemployed* and suggests that Internet users have lower loneliness scores (-0.1214, p<.001). *EMPLOY* is now interpreted as the difference in loneliness between the employed and unemployed *among those who do not report using the Internet*. This coefficient (-0.0507, p<.01) suggests that those who are employed report lower loneliness scores. A significant interaction is found between Internet use and employment status (0.0564, p<.05) suggesting that employment moderates the effect of Internet use on loneliness scores.

Table 6.4: Interactions between *INTERNET* and *EMPLOY* Predicting Loneliness Scores

		Model L *INTERNET and EMPLOY*	Model M *Main Effects of INTERNET and EMPLOY Interaction*	Model N *Interaction of INTERNET and EMPLOY Over Time*
Fixed Effects	Intercept	0.4895***	0.4924***	0.4926***
	AGE75	0.0043***	0.0043***	0.0042***
	INTERNET	-0.1113***	-0.1214***	-0.1216***
	EMPLOY	-0.0273*	-0.0507**	-0.0509**
	INTERNET x *EMPLOY*		0.0564*	0.0594*
	INTERNET x *EMPLOY* x *AGE75*			0.0016
Variance Components				
Level 1:	Within-person	0.1193***	0.1192***	0.1192***
Level 2:	In initial status	0.1453***	0.1453***	0.1453***
	In rate of change	0.0001	0.0001	0.0001
	Covariance	-0.0003	-0.0003	-0.0003
Goodness-of-fit				
	Deviance	17889.7	17884.5	17884.3
	AIC	17905.7	17902.5	17904.3
	BIC	17965.6	17969.8	17979.2

*p<.05; **p<.01; ***p<.001
N = 9414

This moderation effect is illustrated in Figure 6.4. At younger age groups Internet users report lower loneliness scores compared to non-users. Over time, the growth in

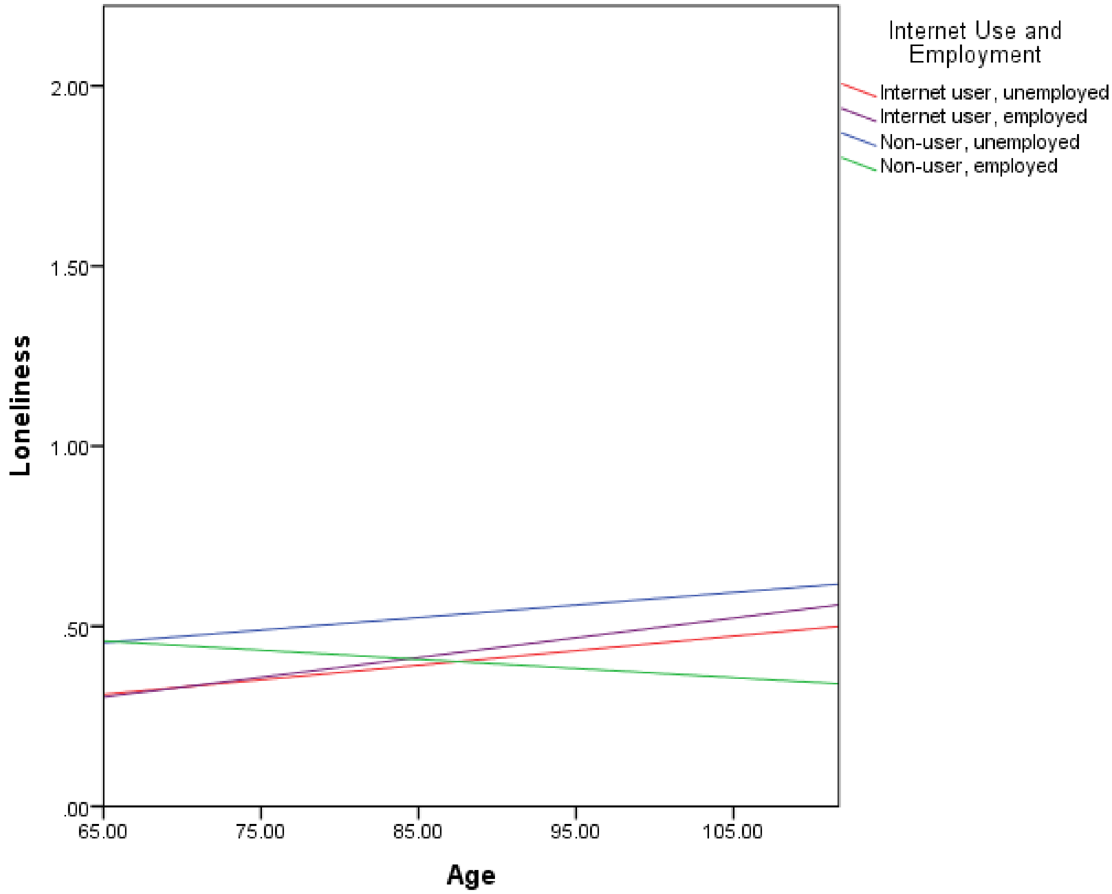

Figure 6.4: Internet Use and Employment Predicting Loneliness Scores

loneliness is similar among all groups (showing a gradual increase in loneliness scores as respondents get older) except for one: Internet non-users who are employed. The growth in loneliness for this group actually shows a *negative slope* such that over time this group reports lower loneliness compared to all other groups. Taken all together, this figure suggests that while Internet use may contribute to lower loneliness scores among HRS respondents, being employed can also be a significant predictor and may contribute to lower loneliness especially among those who do not use the Internet. This is supported by looking at the trajectory of loneliness for those who do not use the Internet and are unemployed: across all age groups, this faction of the HRS dataset report the highest loneliness scores. A final model, Model N, includes a three-way interaction between *AGE75*, *INTERNET*, and *EMPLOY* but was not found to significantly predict loneliness.

Mediation Testing

Prior to examining the potential mediating effects of social integration and social support on the relationship between Internet use and loneliness, growth curve models are estimated for the social integration and social support measures; these results are presented in Table 6.5 and 6.6. Model O examines the main effect of composition of social network (*SOCCOMP*) on loneliness. Time was not a significant predictor of loneliness in this model, however both *INTERNET* and *SOCCOMP* were. On average, Internet users reported lower loneliness scores compared to non-users (-0.0884, p<.001) and having a higher network composition score was associated with decreased loneliness (-0.1616, p<.001). Notably, while network composition was a significant predictor of loneliness, its inclusion did not affect the significance of Internet use as a predictor, suggesting that network composition acts as a partial mediator at best. Model P includes an interaction between *SOCCOMP* and *AGE75*. Interestingly, time became a significant predictor of loneliness with the inclusion of this interaction. Both Internet use and network composition remained significant predictors of loneliness. The interaction of *SOCCOMP* and *AGE75* was also significant suggesting that network composition is a significant predictor of loneliness over time (0.0028, p<.01). On average, the gap in loneliness scores between those with low network composition scores and those with

Table 6.5: Fitting Change Trajectories with Network Composition and Close Relationships to Loneliness Scores

		Model O *Main effect of Network Composition*	Model P *Network Composition predicting growth*	Model Q *Main effect of Close Relationships*	Model R *Close relationships predicting growth*
Fixed Effects	Intercept	1.0266***	1.0569***	0.7776***	0.7900***
	AGE75	0.0003	-0.0088**	-0.0006	-0.0039*
	INTERNET	-0.0884***	-0.0887***	-0.0807***	-0.0807***
	SOCCOMP	-0.1616***	-0.1699***		
	SOCCOMP x *AGE75*		0.0028**		
	CLOSESPOUSE			-0.1047***	-0.1111***
	CLOSESPOUSE x *AGE75*				0.0026***
	CLOSECHILD			-0.0147***	-0.0144***
	CLOSECHILD x *AGE75*				-0.0002
	CLOSEFAM			-0.0065***	-0.0067***
	CLOSEFAM x *AGE75*				0.0001
	CLOSEFRIEND			-0.0203***	-0.0202***
	CLOSEFRIEND x *AGE75*				-0.0000
Variance Components					
Level 1:	Within-person	0.1174***	0.1174***	0.1135***	0.1132***
Level 2:	In initial status	0.1280***	0.1280***	0.1131***	0.1132***

	In rate of change	0.0001*	0.0001*	0.0002*	0.0001*
	Covariance	-0.0003	-0.0003	-0.0001	-0.0000
Goodness-of-fit					
	Deviance	15728.5	15720.4	15384.5	15359.8
	AIC	15744.5	15738.4	15406.5	15389.8
	BIC	15803.6	15804.9	15488.1	15501.0

$^*p<.05$; $^{**}p<.01$; $^{***}p<.001$
N = 9414

high network composition scores increased over time. In this way, having more social connections is associated with a less steep growth of loneliness as an HRS respondent ages.

Model Q in Table 6.5 examines the main effects of close relationships on loneliness scores in HRS respondents. Time is not found to be a significant predictor of loneliness in this model, but Internet use and all four close relationships measures were found to be significant predictors. Regarding Internet use, Internet users reported lower loneliness scores compared to non-users; regarding close relationships, having a close relationship with a spouse and having close relationships with children, other family members, and friends were associated with lower loneliness scores (all $p<.001$). Because *INTERNET* was found to be a significant predictor even when controlling for a variety of close relationships, it appears that close relationships may only partially mediate the relationship between Internet use and loneliness. Model R includes interactions between the close relationship variables and the linear time variable. The only interaction that was found to be significant was between *CLOSESPOUSE* and *AGE75*: the gap in loneliness scores between those who have a close relationship with a spouse and those who do not grows over time (0.0026, $p<.001$) such that the growth in loneliness for those with a close spouse in less steep. Even accounting for these interactions, Internet use remains a significant predictor.

Model S in Table 6.6 examines the main effects of frequency of contact with children, other family, and friends on loneliness. All contact variables had a significant relationship with loneliness such that having increased contact with children, other family, and friends is associated with decreased loneliness. Internet use retained a

Table 6.6: Fitting Change Trajectories with Contact Frequency and Social Support to Loneliness Scores

		Model S *Main effect of Contact Frequency*	Model T *Contact frequency predicting growth*	Model U *Main effect of social support*	Model V *Social support predicting growth*
Fixed Effects	Intercept	0.6866***	0.6900***	1.0023***	1.0107***
	AGE75	0.0036***	0.0022	-0.0009	-0.0031
	INTERNET	-0.0593***	-0.0593***	-0.0771***	-0.0769***
	CONTCHILD	-0.0214***	-0.0243***		
	CONTCHILD x *AGE75*		0.0011		
	CONTFAM	-0.0130**	-0.0121**		
	CONTFAM x *AGE75*		-0.0003		
	CONTFRIEND	-0.0565***	-0.0555***		
	CONTFRIEND x *AGE75*		-0.0003		
	SUPSPOUSE			-0.1147***	-0.1213***
	SUPSPOUSE x *AGE75*				0.0027***
	SUPCHILD			-0.0636***	-0.0657***
	SUPCHILD x *AGE75*				0.0009
	SUPFAM			-0.0373***	-0.0345***
	SUPFAM x *AGE75*				-0.0009
	SUPFRIEND			-0.0725***	-0.0703***
	SUPFRIEND x				-0.0010

	AGE75				
Variance Components					
Level 1:	Within-person	0.1164***	0.1165***	0.1128***	0.1125***
Level 2:	In initial status	0.1356***	0.1356***	0.1066***	0.1069***
	In rate of change	0.0001*	0.0001*	0.0001*	0.0001*
	Covariance	-0.0004	-0.0004	0.0000	0.0001
Goodness-of-fit					
	Deviance	16818.6	16815.2	15266.4	15234.4
	AIC	16838.6	16841.2	15288.4	15264.4
	BIC	16913.1	16938.1	15370.1	15375.8

$^*p<.05$; $^{**}p<.01$; $^{***}p<.001$
$N = 9414$

significant relationship with loneliness even when controlling for the frequency of contact variables, with Internet users reporting lower loneliness scores (-0.0593, $p<.001$). Model T adds interactions between the contact variables and *AGE75*, although none of these interactions were found to be significant – frequency of contact with children, other family members, and friends do not significantly affect loneliness scores over time. Internet use remained a significant predictor of initial status (-0.0593, $p<.001$).

Model U in Table 6.6 examines social support as a predictor of loneliness. Time was not found to have a significant association with loneliness, however Internet use and all four social support measures were found to be significantly associated with loneliness: on average, being an Internet user and reporting increased social support from a spouse, children, other family, and friends were associated with decreased loneliness. Model V includes interactions between the social support measures and *AGE75*, however the only significant interaction was found between social support of spouse and time (0.0027, $p<.001$). On average, the gap in loneliness between those with low or no support from a spouse and those with high support grows over time, suggesting that having increased social support from a spouse is more advantageous over time with regards to loneliness. Even when accounting for these interactions, Internet use was found to be a significant predictor of initial status in loneliness (-0.0769, $p<.001$). This suggests that social support may only partially mediate the relationship between Internet use and loneliness.

The growth curve models previously presented suggest that social integration and social support act only as partial mediators in the relationship between Internet use and loneliness, however these models do not directly test for mediation. Mediation testing is done to estimate the indirect and total effects of Internet use on loneliness when

Table 6.7: Indirect and Total Effects of Internet Use on Loneliness Scores

	Average	*Standard Error*	*Lower Confidence Limit*	*Upper Confidence Limit*
SOCCOMP				
Indirect Effect	0.1301***	0.0173	0.0962	0.1641
Total Effect	0.3306***	0.0317	0.2686	0.3927
CLOSESPOUSE				
Indirect Effect	-0.0098	0.0056	-0.0208	0.0012
Total Effect	-0.1076**	0.0382	-0.1825	-0.0326
CLOSECHILD				
Indirect Effect	-0.0471	0.0653	-0.1751	0.0810
Total Effect	-0.4167***	0.0898	-0.5927	-0.2406
CLOSEFAM				
Indirect Effect	-0.0840	0.0905	-0.2613	0.0933
Total Effect	0.3663**	0.1149	0.1411	0.5916
CLOSEFRIEND				
Indirect Effect	0.0165	0.0502	-0.0819	0.1149
Total Effect	0.5234***	0.0602	0.4055	0.6413
CONTCHILD				
Indirect Effect	0.1700***	0.0196	0.1316	0.2083
Total Effect	0.2497***	0.0305	0.1898	0.3095
CONTFAM				
Indirect Effect	0.0668***	0.0182	0.0312	0.1023
Total Effect	0.7184***	0.0305	0.6586	0.7781
CONTFRIEND				
Indirect Effect	-0.3039***	0.0752	-0.4513	-0.1565
Total Effect	0.7732***	0.2133	0.3551	1.1912
SUPSPOUSE				
Indirect Effect	0.0046	0.0100	-0.0151	0.0243
Total Effect	0.0132	0.0200	-0.0261	0.0524
SUPCHILD				
Indirect Effect	0.0022	0.0188	-0.0347	0.0392
Total Effect	-0.0976***	0.0275	-0.1514	-0.0437
SUPFAM				
Indirect Effect	-0.0237***	0.0039	-0.0314	-0.0159
Total Effect	0.1077***	0.0204	0.0678	0.1477
SUPFRIEND				
Indirect Effect	0.0621***	0.0017	0.0588	0.0654
Total Effect	0.1837***	0.0174	0.1496	0.2178

Confidence limits reflect 95% confidence intervals

N = 9414

accounting for mediators. As with the depressive symptomatology analysis, a significant result for the indirect effect indicates that mediation is occurring and a significant result for the indirect *and* total effect indicates that the mediation is partial. Table 6.7 contains the average indirect and total effects of Internet use on loneliness scores by mediator along with standard errors and 95% confidence intervals. Composition of social network, frequency of contact with children, frequency of contact with family, frequency of contact with friends, social support from family, and social support from friends were all shown to partially mediate the relationship between Internet use and loneliness. No social integration or social support measure was found to fully mediate the association between Internet use and loneliness scores.

To summarize, Internet use is found to be a significant predictor of loneliness for HRS respondents such that Internet users, compared to non-users, report lower levels of loneliness. However, Internet use is not found to be a significant predictor of loneliness over time – while Internet users report less loneliness, the *gap* in loneliness scores between users and non-users does not increase or decrease over time. Internet use remains a significant predictor of loneliness even when accounting for demographic characteristics, moderation effects of demographic measures, social integration and social support measures. Regarding moderation, both income and employment status were found to significantly moderate the relationship of Internet use and loneliness. Regarding social integration and social support, evidence was found to support the notion that composition of social network, frequency of contact with children, frequency of contact with family, frequency of contact with friends, social support from family, and social support from friends mediate the relationship between Internet use and loneliness;

however, evidence suggests the mediation is only partial, indicating that there are aspects of Internet use that affect loneliness independent of social integration and social support.

CHAPTER SEVEN

PERSONAL GROWTH

Personal growth, as defined by Ryff (1995), is a subjective measure of mental well-being that estimates an individual's feelings of personal expansion and improvement. Overall personal growth captures individual feelings of development over time, openness to trying new things and openness to having new experiences, and feelings towards lifelong learning and intellectual advancement. In research, personal growth is often used as a component in estimating and evaluating overall psychological well-being (Ryff 1995, 1989; Ryff and Keyes 1995). Personal growth has become an outcome of interest to aging researchers because studies have shown that personal growth levels tend to be lower for older adults compared to younger age groups and because evidence has shown that individuals with higher feelings of personal growth experience better health outcomes (Ryff 1995; Ryff and Singer 2008). In this chapter, Internet use is examined as a possible predictor of personal growth in older adults; in addition, social integration and social support are examined as potential mediators.

Mediation Testing

As with the life satisfaction analysis presented in Chapter 5, limitations in the HRS dataset prevent longitudinal analysis of the personal growth outcome. In the HRS personal growth is measured only once in the 2006 wave. As such, mediation testing is conducted using the Baron and Kenny method (1986) using OLS regression. Table 7.1 presents the results of the first step of mediation testing where Internet use is regressed on each potential mediator. Overall, Internet use was found to be a significant positive predictor of composition of social network, close relationships with spouse, close relationships with friends, contact with children, contact with family, contact with friends, and social support from spouse. Internet use was also found to be a significant negative predictor of close relationships with children, close relationships with family, and social support from family. No significant relationship with either social support from children or social support from friends was found (as such, these are dropped from future models).

Table 7.1: Internet Use as a Predictor of Social Integration/Support (OLS Regression, HRS 2006)

Mediator	Relationship with Internet Use
SOCCOMP	0.237*** (0.023)
CLOSESPOUSE	0.448*** (0.043)
CLOSECHILD	-0.262*** (0.061)
CLOSEFAM	-0.537*** (0.095)
CLOSEFRIEND	0.334** (0.101)
CONTCHILD	0.546*** (0.037)
CONTFAM	0.271*** (0.036)
CONTFRIEND	0.749*** (0.036)
SUPSPOUSE	0.444*** (0.042)
SUPCHILD	-0.027 (0.029)
SUPFAM	-0.176*** (0.031)
SUPFRIEND	0.047 (0.029)

OLS coefficients (with standard deviations) presented; *p<.05; **p<.01; ***p<.001

Comparing Table 7.1 with Table 5.1 (for review, see Chapter 5) it appears that the relationships between Internet use and the mediators were similar in significance and direction (if not exact magnitude), except in the case of social support from friends. In the 2012 sample used in the Chapter 5 analysis of life satisfaction, Internet use was a significant predictor of social support from friends such that Internet users reported increased support (0.112, *p*<.01). However, in the 2006 sample no significant relationship was found between Internet use and social support from friends. However, all other relationships remain relatively consistent between 2006 and 2012.

Table 7.2 shows the results of the mediation testing. As the second step of testing according to Baron and Kenny (1986) involves observing the relationship between the predictor and outcome, Model A presents the regression results wherein personal growth is regressed on Internet use in the absence of any mediators. Internet use is found to have a significant, positive relationship with personal growth (0.511, *p*<.001), with Internet users reporting higher personal growth scores compared to non-users (based on a scale of 0-5, with 5 = high feelings of personal growth).

Model B in Table 7.2 incorporates the social integration measures into the regression. Integration measures with a significant positive association with personal growth include close relationships with spouse, close relationships with family, close relationships with friends, contact with children, and contact with friends. For all these measures, increased social integration was associated with increased feelings of personal growth. Internet use retained a significant relationship with personal growth such that users reported higher personal growth scores. While social integration did appear to mediate the relationship between Internet use and personal growth, the mediation was relatively small (30%) compared to the effects found in Chapter 5.

Model C takes out the social integration measures and incorporates the social support measures into the regression. Both social support measures had a significant, positive

Table 7.2: Internet Use and Social Integration/Support Predicting Personal Growth (OLS Regression, HRS 2006)

Predictor	Model A *INTERNET*	Model B *INTERNET and Social Integration*	Model C *INTERNET and Social Support*	Model D *Full model*
INTERNET	0.511***	0.356***	0.516***	0.378***
	(0.030)	(0.031)	(0.030)	(0.032)
SOCCOMP		-0.031		-0.060
		(0.030)		(0.031)
CLOSESPOUSE		0.044**		0.025
		(0.014)		(0.026)
CLOSECHILD		-0.007		-0.009
		(0.009)		(0.009)
CLOSEFAM		0.013*		0.007
		(0.006)		(0.006)
CLOSEFRIEND		0.033***		0.031***
		(0.005)		(0.005)
CONTCHILD		0.034*		0.043**
		(0.014)		(0.014)
CONTFAM		0.001		-0.050**
		(0.014)		(0.016)
CONTFRIEND		0.153***		0.158***
		(0.014)		(0.014)
SUPSPOUSE			0.032**	0.032
			(0.011)	(0.027)
SUPFAM			0.123***	0.113***
			(0.015)	(0.018)
Adjusted R^2	0.069	0.142	0.087	0.150

OLS coefficients (with standard deviations) presented ; *p<.05; **p<.01; ***p<.001
N = 3943

relationship with the outcome, however Internet use retained a significant relationship with the outcome. Interestingly, the coefficient for *INTERNET* actually increased between Model A and Model C by 0.005 points.

Model D reintroduces the social integration measures and examines Internet use, social integration, and social support as predictors of personal growth. Close relationships with friends, all contact measures, and social support from family showed a significant association with personal growth. Internet use retained a significant relationship with the outcome such that Internet users, compared to non-users, scored 0.378 points higher in personal growth.

Including Demographic Measures

Table 7.3 presents a final, full model wherein demographic characteristics are included in the regression. Of the demographic variables, all were significantly associated with personal growth. Being younger, female, more educated, non-white, having higher income, being employed, having better self-rated health, and having low functional limitations were associated with better personal growth scores. Having close relationships with friends, increased contact with friends, and social support family were associated with increased personal growth whereas composition of social network was actually associated with decreased scores. Despite controlling for all of these demographic variables and mediators, Internet use remained a significant predictor of personal growth such that users reported higher scores compared to non-users. Review of the R^2 statistics between the models in Table 7.2 and 7.3 reveal that the full model is the best fitting model. That said, compared to the results in Chapter 5, it appears that Internet use is a much stronger predictor of personal growth than life satisfaction.

Table 7.3: Full OLS Regression Model Predicting Personal Growth (HRS 2006)

Predictor	Relationship with Life Satisfaction
INTERNET	0.199***
	(0.033)
SOCCOMP	-0.072*
	(0.030)
CLOSESPOUSE	0.022
	(0.025)
CLOSECHILD	0.000
	(0.008)
CLOSEFAM	0.005
	(0.005)
CLOSEFRIEND	0.029***
	(0.005)
CONTCHILD	0.033*
	(0.014)
CONTFAM	-0.037*
	(0.016)
CONTFRIEND	0.127***
	(0.014)
SUPSPOUSE	0.019
	(0.027)
SUPFAM	0.108***
	(0.018)
AGE	-0.008***
	(0.002)
SEX	0.076**
	(0.029)
EDUCATION	0.045***
	(0.005)

RACE	0.189***
	(0.040)
INCOME	0.011*
	(0.005)
EMPLOY	0.076*
	(0.035)
HEALTH	0.128***
	(0.014)
FUNCTION	-0.082**
	(0.030)
Adjusted R^2	0.218

OLS coefficients (with standard deviations) presented ; *p<.05; **p<.01; ***p<.001
N = 3913

CHAPTER EIGHT

PURPOSE IN LIFE

Purpose in life, like personal growth, is a subjective measure of psychological well-being that estimates an individual's feelings towards life goals and meaning (Ryff 1995; Ryff and Keyes 1995). Purpose in life measurement takes into account an individual's goal-setting and activeness in achieving these goals as well as overall feelings of life direction. As with personal growth presented in the previous chapter, purpose in life tends to be lower in older adults compared to young adults and middle-aged adults and has become a focus of aging researchers due to its association with better health (Ryff 1995; Ryff and Singer 2008). In this final analysis chapter, Internet use is examined as a possible predictor of purpose in life and social integration/support are examined as possible mediators in this relationship.

Unlike the personal growth outcome, purpose in life was measured in the HRS in multiple waves (2006, 2008, 2010, and 2012). However, as detailed more thoroughly in Chapter 3, each individual in the HRS that answered the purpose in life questions can only have a maximum of 2 time points – the sub-samples that answered the purpose in life questions either answered them in 2006 and 2010 *or* answered them in 2008 and 2012. As such there are essentially two sub-samples with purpose in life data, each with two time points. Because growth curve modeling is not recommended with less than three time points (Singer and Willett 2003), OLS regression is instead used to test for mediation per the instructions outlined by Baron and Kenny (1986). In addition, the analyses are done *separately* for the 2006/2010 sub-sample (referred to as the 2010 sample from this point forward) and the 2008/2012 sub-sample (referred to as the 2012 sample), as combining the samples may hide potential period effects (although, given the rather small spacing of time points, period effects are not expected).

Mediation Testing

Table 8.1 includes the regression results that test the relationship between Internet use and the social integration and social support measures. As suggested by Baron and Kenny (1986), this step determines if the primary predictor has a significant relationship with any mediators and helps determine what mediators, if any, to include in future models. The testing is done separately for the 2010 and 2012 sample (note that the analysis done for the 2012 sample is the same that was done in Chapter 5 for the life satisfaction investigation). All but one of the potential mediators was found to have a significant relationship with Internet use. Only social support from children did not have a significant relationship in either the 2010 nor the 2012 sample (as such, it is dropped from future models). Of the significant relationships, Internet use had positive associations with composition of social network, close relationships with spouse, close relationships with friends, all contact variables, social support from spouse, and social support from friends. Internet use has a negative association with close relationships with children, close relationships with family, and social support from family. Between the two samples the coefficients were relatively close in magnitude and in the same direction.

Table 8.1: Internet Use as a Predictor of Social Integration/Support (OLS Regression)

Mediator	2010 Sub-Sample	2012 Sub-sample
SOCCOMP	0.252*** (0.026)	0.238*** (0.029)
CLOSESPOUSE	0.451*** (0.049)	0.417*** (0.052)
CLOSECHILD	-0.246*** (0.064)	-0.358*** (0.070)
CLOSEFAM	-0.651*** (0.103)	-0.496*** (0.109)
CLOSEFRIEND	0.415*** (0.111)	0.317** (0.113)
CONTCHILD	0.683*** (0.042)	0.620*** (0.043)
CONTFAM	0.350*** (0.041)	0.281*** (0.043)
CONTFRIEND	0.833*** (0.040)	0.885*** (0.042)
SUPSPOUSE	0.475*** (0.048)	0.447*** (0.050)
SUPCHILD	-0.043 (0.032)	-0.052 (0.033)
SUPFAM	-0.172*** (0.035)	-0.168*** (0.036)
SUPFRIEND	0.082* (0.032)	0.112** (0.033)

OLS coefficients (with standard deviations) presented; *p<.05; **p<.01; ***p<.001

Table 8.2 introduces the purpose in life outcome into the regression models for the 2010 sample. In Model A purpose in life is regressed on *INTERNET* in the absence of any other control variables. Internet use is found to have a positive, significant relationship with purpose in life (0.356, p<.001) such that Internet users score higher on the outcome (on a scale of 0-5, with 5 = increased purpose) compared to non-users. As with all other previous outcomes, in the absence of mediators and controls it appears Internet users enjoy elevated mental well-being compared to non-users.

Model B introduces the social integration variables. Having a close relationship with spouse, close relationships with friends, and increased contact with family and friends were all significantly associated with increased feelings of purpose in life. Internet use retained a significant relationship with purpose in life despite controlling for social integration, although the effect is smaller. Overall, social integration mediated the relationship between Internet use and purpose in life by 52%.

Table 8.2: Internet Use and Social Integration/Support Predicting Purpose in Life (OLS Regression, HRS 2010)

Predictor	Model A *INTERNET*	Model B *INTERNET and Social Integration*	Model C *INTERNET and Social Support*	Model D *Full model*
INTERNET	0.356*** (0.036)	0.170*** (0.038)	0.307*** (0.035)	0.213*** (0.039)
SOCCOMP		-0.008 (0.037)		-0.072 (0.037)
CLOSESPOUSE		0.091*** (0.018)		0.015 (0.034)
CLOSECHILD		-0.004 (0.011)		-0.003 (0.011)
CLOSEFAM		0.013 (0.007)		0.007 (0.007)
CLOSEFRIEND		0.036*** (0.006)		0.028*** (0.006)
CONTCHILD		0.032 (0.017)		0.043* (0.017)
CONTFAM		0.040* (0.017)		0.008 (0.020)
CONTFRIEND		0.122*** (0.017)		0.078*** (0.019)
SUPSPOUSE			0.105*** (0.013)	0.112** (0.035)
SUPFAM			0.088*** (0.018)	0.075** (0.023)
SUPFRIEND			0.221*** (0.020)	0.129*** (0.024)
Adjusted R^2	0.033	0.111	0.111	0.128

OLS coefficients (with standard deviations) presented; **p*<.05; ***p*<.01; ****p*<.001
N = 2929

Model C takes out the social integration measures and replaces them with the social support measures. All three support measures that were included showed a significant association with purpose in life such that increased support was associated with increased purpose in life. The support measures, however, did not mediate the relationship between

Internet use and purpose in life to the same extent that social integration did. Internet use remained a significant predictor of purpose in life and social support mediated this relationship only 14%.

The final model in Table 8.2, Model D, includes both the social integration and social support measures. Of the social integration measures, having close friends, contact with children, and contact with friends positively and significantly related to purpose in life. All three social support measures retained a significant relationship with the outcome, as did *INTERNET*. Overall, Internet users scored 0.213 points higher in purpose in life compared to non-users (p<.001).

Table 8.3 presents the same analytic results as presented in Table 8.2, however in Table 8.3 the results are for the 2012 HRS sample. In general terms the results are consistent in that Internet use remained a significant predictor of purpose in life in all models, even when accounting for the mediators. However, there were slight deviations in which mediators had a significant relationship with purpose in life. In Model B in Table 8.3, all close relationship variables significantly predicted the outcome whereas in Table 8.2 only relationships with spouse and friends were significant; in addition, for the contact variables both children and friends significantly predicted purpose in life in Table 8.3, but in 8.2 it was contact with family and friends that were significant. Both analyses produced similar results for Model C. For Model D, composition of social network and close relationships with children significantly predicted purpose in life for the 2012 sample but not the 2010 sample, and while social support from spouse predicted the outcome in 2010 it did not serve as a significant predictor in 2012. Yet while there were slight differences in the results between the 2010 and 2012 sample, one result remained stable – Internet users reported higher scores for purpose in life.

Table 8.3: Internet Use and Social Integration/Support Predicting Purpose in Life (OLS Regression, HRS 2012)

Predictor	Model A *INTERNET*	Model B *INTERNET and Social Integration*	Model C *INTERNET and Social Support*	Model D *Full model*
INTERNET	0.399***	0.250***	0.354***	0.289***
	(0.037)	(0.040)	(0.037)	(0.040)
SOCCOMP		-0.024		-0.085*
		(0.039)		(0.040)
CLOSESPOUSE		0.075***		0.069
		(0.019)		(0.036)
CLOSECHILD		-0.024*		-0.023*
		(0.011)		(0.011)
CLOSEFAM		0.020**		0.012
		(0.007)		(0.008)
CLOSEFRIEND		0.042***		0.034***
		(0.007)		(0.007)
CONTCHILD		0.039*		0.057**
		(0.018)		(0.018)
CONTFAM		0.032		-0.035
		(0.018)		(0.021)
CONTFRIEND		0.082***		0.053**
		(0.018)		(0.020)
SUPSPOUSE			0.074***	0.033
			(0.014)	(0.036)
SUPFAM			0.124***	0.139***
			(0.019)	(0.025)
SUPFRIEND			0.179***	0.100***
			(0.021)	(0.025)
Adjusted R^2	0.045	0.110	0.110	0.130

OLS coefficients (with standard deviations) presented; *p<.05; **p<.01; ***p<.001
N = 2450

Including Demographic Measures

The final table, Table 8.4, presents results for the 2010 and 2012 sample wherein demographic characteristics are added to the OLS regression. Close relationships with friends, contact with children, social support from friends, age, race, self-rated health, functional limitations, and previous reports of purpose in life were all associated with purpose in life for the 2010 and 2012 samples. Other significant predictors for 2010 included composition of social network, social support from spouse, and education; for 2012, additional significant associations were found for close relationships with children and social support from family. Notably, while Internet use was found to be a significant predictor of purpose in life in the full model for the 2012 sample, it was *not* found to significantly predict purpose in life for the 2010 sample once all demographic characteristics were accounted for. Stepwise regressions (not presented here) were performed to determine if any one demographic characteristic was explaining away the previously found relationship between Internet use and purpose in life; however results did not reveal any one predictor that was accounting for the effect (i.e., nearly all demographic measures diminished the Internet use coefficient to some extent). This result was only found for the 2010 sample, however, as Internet use remained a significant predictor for the 2012 sample.

Table 8.4: Full OLS Regression Model Predicting Purpose in Life

Predictor	2010 Sub-Sample	2012 Sub-Sample
INTERNET	-0.022	0.122**
	(0.036)	(0.037)
SOCCOMP	-0.079*	-0.061
	(0.033)	(0.034)
CLOSESPOUSE	0.001	0.026
	(0.030)	(0.030)
CLOSECHILD	0.010	-0.020*
	(0.010)	(0.010)
CLOSEFAM	-0.002	0.005
	(0.006)	(0.006)
CLOSEFRIEND	0.015**	0.024***
	(0.006)	(0.006)
CONTCHILD	0.044**	0.057***
	(0.015)	(0.015)
CONTFAM	0.017	-0.035
	(0.017)	(0.018)
CONTFRIEND	0.024	-0.003
	(0.017)	(0.017)
SUPSPOUSE	0.064*	0.002
	(0.031)	(0.031)
SUPFAM	0.015	0.101***
	(0.020)	(0.021)
SUPFRIEND	0.083***	0.060**
	(0.021)	(0.022)
AGE	-0.011***	-0.009**
	(0.002)	(0.003)
SEX	-0.012	0.002
	(0.032)	(0.034)

EDUCATION	0.018**	0.011
	(0.006)	(0.007)
RACE	0.211***	0.198***
	(0.046)	(0.047)
INCOME	0.009	0.009
	(0.006)	(0.006)
EMPLOY	0.017	0.074
	(0.042)	(0.044)
HEALTH	0.105***	0.083***
	(0.016)	(0.017)
FUNCTION	-0.086**	-0.095**
	(0.032)	(0.035)
PURPOSELIFE06	0.522***	
	(0.017)	
PURPOSELIFE08		0.514***
		(0.018)
Adjusted R^2	0.413	0.418

OLS coefficients (with standard deviations) presented; $*p<.05$; $**p<.01$; $***p<.001$
N = 2663 (2010), 2294 (2012)

CHAPTER NINE

CONCLUSION

Despite an inconsistent literature for other populations, ICT use has routinely been found to benefit older adults with regards to mental health and mental well-being (Chen and Persson 2002; Choi, Kong, and Jung 2012; Cotten et al. 2012, forthcoming; Ford and Ford 2009; Sum et al. 2008). The purpose of this study was to expand upon this literature to determine (a) if ICTs had an effect on mental health/well-being in older adults in initial status and over time, and (b) to determine if factors of social life, particularly social integration and social support, acted as mediators in this relationship. Objective mental health and subjective mental well-being were operationalized through the use of five different constructs: depressive symptomatology was used to assess mental health, and life satisfaction, loneliness, personal growth, and purpose in life were used to assess mental well-being. Through the use of five waves of the HRS and through the use of both cross-sectional and longitudinal analysis techniques, support was found for some (but not all) of the proposed hypotheses. This chapter summarizes the findings of the previous chapters per hypothesis and concludes with a discussion of the findings as well as proposals for future research to address the limitations of this investigation.

Findings

Overall, while the results of this study support previously completed research investigating the effects of ICTs on older adults, the findings add to the literature by also detailing potential pathways through which use of the Internet may affect mental health and well-being in old age. This section summarizes the findings of Chapters 4-8 as they relate to each proposed hypothesis from Chapter 3.

Mental Health/Well-Being Over Time

Hypothesis 1 argued that mental health/well-being would decrease for older adults over time. This argument was based on previous literature providing evidence that older adults were at risk for unfavorable mental health/well-being outcomes, such as increased depression (for example, see Clarke et al. 2011) and increased loneliness (for example, see Dykstra, van Tilburg, and Gierveld 2005). Regarding the two outcomes in which longitudinal analysis was possible, evidence from this study supported the notion that older adults were at risk for worse outcomes and that age could be a significant predictor: in the initial growth models, depression and loneliness both increased over time. Depression was found to have a curved growth while loneliness was more linear (although this could be due to the way in which loneliness was coded). This initial analysis seemed to suggest that age was a significant predictor of mental health/well-being in old age.

However, as more predictors were added to the growth models it became apparent that age may *not* be a significant predictor of depression and loneliness; when accounting for other demographic characteristics, the relationship between time and the outcome would eventually become non-significant. In this way, while depression and loneliness both increase over time, *time itself is not a significant predictor*, and that changes in these outcomes are more closely associated with changes in other variables (such as self-rated health or functional limitations). When stated this way it is difficult to argue whether or not support was found for Hypothesis 1. As written (that mental health/well-being decreases over time), one could argue that the longitudinal analysis finds support; however, this hypothesis also implies that time thus significantly predicts these outcomes, and support was not found for this.

Because cross-sectional analysis is unable to account for multiple time points, it cannot measure change over time per individual, although it can be used to determine if outcome levels are different between individuals of different ages. In the OLS regressions age was not found to be a significant predictor of life satisfaction (providing some support for the *hedonic treadmill* argument that life satisfaction does not necessarily change over time), however age was found to significantly predict personal growth and purpose in life: for these two outcomes, older age was associated with decreased personal growth and purpose in life scores. Again, because this was cross-sectional analysis it cannot be stated definitively that these outcomes changed over time, but evidence suggests that age was a significant factor.

It is thus somewhat difficult to make a definitive statement regarding mental health/well-being in old age, as the analysis utilized different techniques and thus the interpretations are different. However, as a general summary, this can be said: evidence was found to support Hypothesis 1 for the depression, loneliness, personal growth, and purpose in life outcomes, as the analysis suggests that these outcomes change over time in such a way to suggest that as an individual grows older, they experience worse outcomes. This does not imply, however, that *age itself* is an important factor in predicting these outcomes. As argued by Blazer (2003), mental health/well-being in old age is more of a product of changes in such things as physical/cognitive disability and socioeconomic status. Restated, being physically incapable of performing daily functions, suffering from increased cognitive decline, and having fewer resources to deal with short- and long-term stressors are what contribute to declines in mental health/well-being in old age. No support was found for Hypothesis 1 for the life satisfaction outcome, as it appears that (as argued by Brickman and Campbell, 1971) older adults adapt to changing circumstances in such a way that their overall level of life satisfaction does not change despite negative changes in such things as physical health and income.

Mental Health/Well-Being and Internet Use

Hypothesis 2 argued that Internet users, compared to non-users, would report better mental health/well-being outcomes (in the absence of a time variable). Because testing of this hypothesis does not require time/age to be included in the model, comparison of the longitudinal and cross-sectional analyses is a bit more straight-forward, as the interpretations are quite similar. In the initial models (prior to accounting for any mediators or control variables), support was found for the notion that Internet use benefits the user. For *all five mental health/well-being outcomes,* Internet users were found to score more favorably compared to non-users. Internet users reported lower depression and loneliness while also reporting higher life satisfaction, personal growth, and purpose in life.

Interestingly, in future models the Internet use variable remained a significant predictor of mental health/well-being in all but two instances. For life satisfaction, the relationship between Internet use and the outcome disappeared with the inclusion of the mediators and demographic measures (this will be detailed more thoroughly in a later section). For purpose in life, the relationship between Internet use and the outcome also disappeared when accounting for other variables, *but only for the 2010 sub-sample*. It can thus be argued that Internet users do report better mental health/well-being outcomes, though other variables may explain this relationship in the case of life satisfaction and (possibly) purpose in life. That said, Internet users consistently reported significantly lower depression and loneliness scores as well as increased personal growth. Support is found for Hypothesis 2 that argues better outcomes for Internet users, results which support findings from other studies (for example, Chen and Persson 2002).

The notion that Internet users enjoy better outcomes can be explained a variety of ways. For one, as discussed previously in Chapter 2, the Internet and ICTs in general provide individuals with the tools to more easily identify, manage, and cope with health issues. Websites such as WebMD give individuals easy access to a wealth of information on health problems, both physical and mental, and individuals may more easily diagnose and treat their health issues without the necessity of seeing a physician. ICTs also provide access to applications that can be used for health management, an example being a smartphone application that allows for easy tracking of blood-glucose levels in diabetic individuals. In this way, Internet users may enjoy better mental health/well-being simply because the Internet provides resources that may assist in dealing with such things as severe depressive episodes.

However, as theoretically argued in this paper, Internet users may also enjoy better outcomes as a result of the social interactions that arise from being online and being connected. DiMaggio et al. (2001) argue that the Internet provides the means for individuals to develop new social contacts as well as reinforce already established social relationships. For older adults, this means that the Internet can be used as a means to communicate with friends and family, particularly those who might not live close by, and also provides the means to join social networking sites to meet new people. Websites like Eons.com (which as of this writing is no longer in operation) provides a virtual space for older adults to communicate with new contacts, share experiences and ideas, and grow their social network. From a social integration perspective (as first developed by Durkheim and expanded by others), growing and reinforcing one's social network would have positive effects on mental health/well-being outcomes. DiMaggio et al. (2001) also argue that the Internet may have the opposite effect, that social integration and social support would diminish through use of the Internet. In the social integration perspective this would, in turn, have negative effects on mental health/well-being. The results here show that Internet users report better health, and thus it seems more likely that social integration and social support are increasing for Internet users, rather than diminishing. This is just an assumption, however, until the actual social integration and social support mediators are added to the analyses.

Trajectory of Mental Health/Well-Being and Internet Use

Hypothesis 3 argued that the trajectory of mental health/well-being would be more favorable for Internet users compared to non-users. Put another way, the gap in mental health/well-being scores between Internet users and non-users would grow over time. Support for this hypothesis would essentially show that Internet use was not only a significant predictor of the outcome, but was also a significant predictor of the outcome *over time*. Because this hypothesis requires longitudinal data to answer adequately, the results from the depression and loneliness chapters only can be used.

Previous work by Cotten et al. (forthcoming) using multiple waves of the HRS found that Internet use significantly reduced the probability of depressive categorization by 33%. A strength of the methodology used in this study is that the analyses was able to account for past states of depression, and thus a significant finding of reduced depressive categorization among Internet users shows an effect of Internet use even when controlling for previous depressive states. However, while this study uses multiple waves of data in the analysis it does not incorporate a meaningful *time* variable and an interaction of time with Internet use. Thus while the results of the work by Cotten et al. supports the findings of this study (that suggests that Internet users report lower depression scores), their work does not accurately reveal the trajectory of depressive symptoms and how this trajectory may be affected by Internet use in the HRS. In this way the results of this study make a significant contribution to the discussion of Internet use and depression in older adults.

While Internet use was found to significantly predict initial status of both depressive symptoms and loneliness, when an interaction with time was included in the growth models the interaction was not found to be significant in either case. Put another way, Internet users consistently reported lower depression and loneliness scores, however the gap in scores between Internet users and non-users neither significantly increased nor decreased. Internet use was thus not found to predict the outcomes over time. This was best illustrated in Figures 4.2 (depressive symptomatology) and 6.2 (loneliness), as when the trajectories of the outcomes were plotted for Internet users and non-users the slopes were similar, similar enough that no statistical difference in slopes was found. In summary, Internet users reported more favorable depression and loneliness scores, however it does not appear that there is increased benefit over time – the trajectories for growth were essentially the same when compared to non-users. Support was not found for Hypothesis 3, indicating that while there may be a benefit to using the Internet in old age, the benefit may not be additive over time for these outcomes.

Social Integration as a Mediator

Based on the theoretical argument that Internet use would increase the quantity and diversity of social relationships, which would in turn positively impact mental health/well-being in old age, Hypothesis 4 argued that social integration would act as a partial mediator in the relationship between Internet use and each of the five outcomes. The results were quite diverse, but evidence shows that certain measures of social integration did significantly mediate the relationship between Internet use and mental health/well-being. A summary is presented in Table 9.1.

Composition of social network. The composition of social network variable measured the diversity in social relationships an individual reported – should a respondent report having contacts in multiple social circles (i.e., through marriage, friends, etc.) their composition score would be higher. Composition of social network did significantly predict all five outcomes (although it should be noted that for life satisfaction significance was found in full models only, and for purpose in life the results were significant only for the 2010 sub-sample). Of particular interest is the result found for

Table 9.1: Summary of Mediation Results

Mediator	Depressive Symptoms	Life Satisfaction	Loneliness	Personal Growth	Purpose in Life
SOCCOMP	+	-	+	-	-
CLOSESPOUSE	-	+	-	+	+
CLOSECHILD	-	+	-	-	-
CLOSEFAM	-	-	-	+	-
CLOSEFRIEND	-	-	-	+	+
CONTCHILD	+	-	+	+	+
CONTFAM	+	-	+	-	+
CONTFRIEND	+	+	+	+	+
SUPSPOUSE	-	+	-	+	+
SUPCHILD	-	-	-	-	-
SUPFAM	+	+	+	+	+
SUPFRIEND	+	+	+	-	+

+at least partial mediation occurs, - no significant mediation effect

loneliness: not only did network composition predict loneliness (such that more diverse networks = lower loneliness scores), but network composition also predicted loneliness *over time*. Having a diverse network contributed to a more favorable loneliness trajectory such that an individual's increase in loneliness over time would be less steep.

The finding that having a diverse network may contribute to decreased loneliness coincides with similar results of a study conducted by Litwin and Shiovitz-Ezra (2011). In their research, Litwin and Shiovitz examined different types of social networks and their relationships with well-being measures of loneliness, anxiety, and happiness, and they found that having a diverse social network was significantly associated with decreased loneliness scores. This paper adds to this finding by showing that a diverse network appears to have additive favorable effects over time. From a theoretical perspective, this relationship makes sense. As argued by Durkheim, as societies move towards modernity there is a rise in individualism such that people become more reliant on one another to fulfill daily tasks. Having a diverse network becomes a resource through which individuals may access social ties with an abundance of different functions. A diverse network gives an individual access to different people who can help accomplish different tasks. It would thus make sense that a diverse network would decrease loneliness – loneliness is a perceived absence of social relationships, and an individual would be less likely to *feel* lonely if there are diverse ties that help fulfill a variety of physical and emotional needs.

With regards to mediation, evidence was found that composition of social network mediated the relationship of Internet use with depression and loneliness, but only partially (as hypothesized). In the cross-sectional mediation testing, however, the results did not appear to support a mediation effect. While Internet use did predict the outcomes, models predicting life satisfaction, personal growth, and purpose in life did not show that composition mediated the effects. In the case of life satisfaction, neither Internet use nor network composition were significant predictors in the mediation test. While having a diverse network appears to contribute to depression and loneliness, it does not appear to have an effect on global satisfaction. This may be because older adults are, in some ways, adaptable to their social environments, and it is possible that they grow accustomed to their network composition to the point that it does not affect life satisfaction (this indirectly supports the *hedonic treadmill* model of life satisfaction – older adults are adaptable to their circumstances). While it was hypothesized that social integration would impact life satisfaction, diversity of social networks may be an aspect of integration that is less important.

For personal growth and purpose in life, Internet use remained significant but network composition was not. While evidence was found to suggest that Internet use could contribute to a more diverse network, these increases through Internet use did not significantly impact personal growth and purpose in life. Having a diverse social network provides an individual additional avenues to procure resources, but these results imply that being able to procure these varied resources are less important for personal growth and purpose in life. It could be that, because personal growth and purpose in life are constructs that focus on *individual development*, older adults are less influenced by varied ties, as these ties are more about the people *around* the individual rather than the individual him/herself.

Close relationships. Close relationships were measured by asking HRS respondents to state how close they were to their spouse/partner and to also indicate how many children, family, and friends they have close relationships with. Better relationships with spouse/partner and more close relationships with children, family, and friends contributed to higher relationship scores. Close relationships with spouse/partner predicted all five outcomes. Close relationships with children predicted life satisfaction, loneliness, and purpose in life. Close relationships with other family members predicted loneliness and personal growth. Finally, close relationships with friends predicted depression, loneliness, personal growth, and purpose in life.

Regarding the longitudinal analyses (depression and loneliness), only close relationships with friends significantly predicted depression over time, and none of the close relationships variables predicted loneliness over time. For friends, it appears that having more close friends contributed to a less steep depression trajectory over time (i.e., the gap in depression scores grows bigger over time based on number of close friends, with those with more friends reporting decreased depression). While there is a literature that suggests that older adults are less inclined to attempt developing new friendships in old age due in part to the stress and exertion needed to do so, this same literature also argues that this forces older adults to rely more heavily on an established core network (for example, see Potts 1997), and thus a lack of close friends in this network (and thus a lack of physical and/or emotional resources available from these friendships) may contribute to higher levels of depression. The finding that close relationships with friends significantly predicts depression over time supports this notion.

While it appears close relationships do contribute to mental health/well-being, Internet use may not be affecting these relationships to the point that mental health/well-being is affected. Put another way, results do not suggest that close relationships act as strong mediators. For depression, *none* of the close relationship variables mediated the effect of Internet use on depression – the pathway through which Internet use affects depression does not appear to be through close relationships. A possible explanation for this finding is that while Internet use has the potential to give older adults a means to communicate with networks and establish new relationships, Internet use might not be actually *increasing* the number of close relationships (or, for the case of spouse/partners, increasing the closeness of the relationship) that are important for preventing depression.

Internet use may allow older adults to contact close family and friends, but not increase the number of family and friends who are deemed "close" enough to provide physical and emotional resources that help alleviate depressive symptoms. In addition, if older adults are using the Internet to meet new people, it could be that the relationships that are established online are weaker ties that the individual would not deem "close." This can serve as a possible explanation as to why Internet use and close relationships were both found to predict depression, but that no support was found for the pathway of Internet use → close relationships → depression. A similar result was found for loneliness, with none of the close relationship variables serving as significant mediators.

For life satisfaction, close relationships with spouse/partner and children acted as mediators, again to the point that Internet use was no longer a significant predictor of the outcome. This is an interesting finding in that close relationships with a spouse/partner and children tend to be viewed as stronger bonds, or stronger ties, than other family and friends, and while there is a literature to suggest that the Internet can be used to strengthen bonds between people it is more often seen among weaker ties (Ellison et al. 2007). Also interesting is the fact that *complete* mediation was found for these variables, rather than the hypothesized partial, indicating that there was no significant direct effect of Internet use on life satisfaction; the effect of Internet use is explained almost entirely by close relationships with spouse/partner and children. What this seems to indicate is that the other functions of Internet use, such as for information-seeking, do not affect life satisfaction, and that one of the Internet's primary avenues in influencing life satisfaction is through changes in close relationships. A possible explanation as to why these relationships were important mediators goes back to the findings of s study conducted by

Chen (2001) examining life satisfaction among Taiwanese elderly. Chen found that those with unfavorable living arrangements in old age (such as living alone) reported lower life satisfaction and implied that these individuals "…did not gain needed support from their families" (2001: 76). While other theories of aging (such as activity and continuity theories, for example see Atchley 1989) theorize about the importance of social activities with weaker ties in helping determine life satisfaction, the results of Chen and the findings of this paper seem to suggest that closer ties are also important.

Relationships with spouse/partner, family, and friends mediated the effects of Internet use for the personal growth outcome while relationships with spouse/partner and friends mediated the effects of Internet use for purpose in life. Because both of these outcomes are subjective measures linked to feelings of personal development, it is likely that an individual's self-assessment is based on comparisons with like individuals; this would explain why close relationships with children was not found to be a significant mediator in either case, as (compared to the other groups) children would belong to a younger cohort than the respondent and lack personal experiences that would make their lives apt for comparison. It is more likely older adults would assess their personal growth and purpose in life based on experiences of spouse/partners as well as family/friends that are of similar age and circumstance. However, this does not explain why close relationships with family were found to be significant mediators for personal growth but not purpose in life. While Internet use was found to significantly predict close relationships with family, this relationship does not serve as a significant avenue through which purpose in life is significantly affected. It could be that family relations are less important in determining personal feelings of meaning in life, although the reason is not entirely clear and needs to be further teased out.

Contact with social network. A final set of social integration variables examined how frequently HRS respondents contacted specific ties in their social network (children, family, and friends) through the use of various communication methods including telephone and email. Increased frequency of contact translated to an increased contact score. Contact with children and friends predicted depression and personal growth while only contact with friends predicted life satisfaction. All three contact variables predicted loneliness and purpose in life. In this way it appears that, among the contact mediators, contact with friends was the most prevalent predictor of mental health/well-being in the HRS, as it was the only contact measure that significantly predicted all five outcomes.

For the longitudinal analyses, all three contact variables significantly mediated the effect of Internet use on depression and loneliness, but only partially. Considering the communication potential of the Internet, this is expected, as being online would likely increase the opportunities to reach out to various different networks. These increased opportunities would also increase the potential for social contacts in these networks to be able to provide resources to help deal with depression and loneliness.

Contact with friends helped mediate the effect of Internet use on life satisfaction to the point that Internet use was no longer a significant predictor. This is interesting in the sense that, in predicting life satisfaction, while closeness with spouse/partner and children were important for the close relationships measures, of the contact variables it was friends (and not spouse/partner or children) that were important. What this possibly entails is that, for life satisfaction, it is possible that older adults gather more *emotional* support from spouse/partner and children and possibly more *practical* support from friends, which would explain the differences in results. Contact with children and friends were significant mediators in the personal growth analysis but, again, the mediation effect was only partial. That same can be said for purpose in life, where all three contact variables were significant mediators.

In conclusion, support is found for Hypothesis 4 that suggests that social integration acts as a mediator in the relationship between ICT use and mental health/well-being in old age. While the results vary depending on the outcome as well as the mediator examined, generally speaking it appears that Internet use has a significant relationship with social integration, which in turn has a significant relationship with objective mental health and subjective mental well-being. An important note is that of all social integration measures, only frequency of contact with friends was found to be a significant mediator across *all* outcomes, pointing to the importance of being able to converse with friends and the potential role Internet use plays in making this happen.

Social Support as a Mediator

While social integration measures the quantity and diversity of social relationships, social support measures the quality of social ties. Hypothesis 5 argues that social support, like social integration, would partially mediate the effects of Internet use on mental health/well-being. As with the social integration measures, results were mixed depending on the outcome and the social support measure examined. A summary is presented in Table 9.1.

For depression, all four social support measures (support from spouse/partner, children, family, and friends) significantly predicted the outcome such that increased support predicted lower depression scores. However, none of the support measures was found to predict depression over time (i.e., there was no interaction with age). There was no additive effect over time of social support on depression. This implies that social support may be an important component in dealing with current depression, but social support levels might not be important for *future* levels of depression. As for the mediation testing, only support from family and friends mediated the relationship between Internet use and depression, and only partially. Interpreted another way, the effect of Internet use on depression could be partially attributed to increases in social support from family and friends. Interestingly, when comparing the sources of support, one would most likely argue that ties with a spouse/partner and ties with children would be stronger than ties with other family and with friends. It would thus appear that the avenue through which Internet affects depression is through a *strengthening of social support through weak ties*. In social capital literature, weak ties provide bridging capital that allows individuals to access a variety of diverse resources, and previous studies have found that Internet use can contribute to the development of weak tie-based social networks (for example, see Ellison et al. 2007). Family and friendship networks tend to be more diverse than spousal and child-based networks, and would be more likely to be significantly affected by Internet use. Taken together, it is not surprising that family- and friend-based support acts as mediators, as social integration and social capital theoretical arguments dictate that it would be more likely for the Internet to affect depression through changes in weak ties. This is not to say that spousal/partner and child relationships are not important in predicting depression; quite the contrary, the growth curve models found that these support measures significantly predicted depressive symptoms. However, it does not appear that the effect of Internet use on the outcome is through these measures.

The results were nearly identical for loneliness in that all four support measures predicted the outcome but only support from family and friends served as significant mediators. Interestingly, social support from a spouse/partner was also found to significantly predict loneliness over time such that the gap in loneliness increased between those with little support and those with increased support. Considering the protective effect of marriage on health and the stress that is often experienced when entering widowhood, this result is expected and has been found in other studies (see for example, Savikko et al. 2005).

For the cross-sectional analysis, support from spouse/partner, family, and friends mediated the relationship between Internet use and life satisfaction, but only partially (as Internet use still significantly predicted life satisfaction when controlling for social support). Why social support from children did not serve as a significant mediator is unclear, although a possible explanation is that because activity/continuity theories of aging dictate that life satisfaction can be influenced by social experiences, it may be that the social experiences of other groups (those of similar ages and circumstances) are more vital than those of children. The same was found for purpose in life. For personal growth, only support from spouse/partner and family partially mediated the relationship. Again, personal growth can be heavily influenced by an individual's comparison with those that are like them, and so social support from children might not be as vital a factor (as children would be dissimilar with regards to age and experiences). However, this does not explain a lack of mediation effect for social support from friends.

Other Predictors of Mental Health/Well-Being

In addition to the primary predictor and mediators, other demographic characteristics were included in the analytic models to determine what other factors might affect mental health/well-being in old age as well as determine if these factors may explain away previously significant relationships of Internet use and/or mediators with the outcomes. Results were mixed, once again, depending on the outcome of interest. A summary of the results of the demographic variables predicting the outcomes is presented in Table 9.2, while Table 9.3 contains a summary of the moderation analyses.

For depressive symptomatology, significant demographic predictors of the outcome included sex, education, income, employment status, self-rated health, and functional limitations. However, inclusion of these factors into the growth curve model did not explain away all of the effect of Internet use on CES-D scores in the HRS sample, as Internet users were still found to report lower depression scores compared to non-users (and this difference was significant at the $p<.001$ level). Interestingly, significant interaction effects were found between Internet use and four of the demographic measures: income, employment status, self-rated health, and functional limitations. These interactions are detailed more thoroughly in Chapter 4, but the general finding is that Internet use typically translated into a more favorable depression trajectory.

In contrast to depressive symptomatology, where most demographic measures significantly predicted the outcome, for life satisfaction only two demographic measures

Table 9.2: Summary of Demographic Predictors

Variable	Depressive Symptoms	Life Satisfaction	Loneliness	Personal Growth	Purpose in Life
AGE	-	-	-	+	+
SEX	+	-	+	+	-
EDUCATION	+	-	+	+	+
RACE	-	-	-	+	+
INCOME	+	-	+	+	-
EMPLOY	+	-	+	+	-
HEALTH	+	+	+	+	+
FUNCTION	+	-	+	+	+

+significant relationship found in full model, - no significant relationship found

significantly predicted the outcome: self-rated health and previous reports of life satisfaction levels. However, inclusion of these characteristics did drastically improve model fit; between the model that only included the Internet use/mediators and the full model the R^2 increased from 0.069 to 0.238 (representing a change of 0.169). Put another way, while most of the demographic measures did not significantly predict life satisfaction, inclusion of these variables explained approximately 17% more of the variance compared to the model where only Internet use and the mediators were examined. Also of note is that the coefficient for Internet use in the final regression model was reduced to 0.004 – when taking into account demographic characteristics, the effect of Internet use on life satisfaction was non-significant and almost nonexistent.

Table 9.3: Summary of Moderation Results in Longitudinal Analyses

Moderator	Depressive Symptoms	Loneliness
SEX	-	-
EDUCATION	-	-
RACE	-	-
INCOME	+	+
EMPLOY	+	+
HEALTH	+	-
FUNCTION	+	-

+moderation effect found with Internet use, - no significant moderation effect

For loneliness, only race was not found to be significantly associated with the outcome. All others, including sex, education, income, employment status, self-rated health, and functional limitations significantly predicted loneliness, although in these models Internet use retained a significant relationship with the outcome. Interactions were examined between Internet use and the demographic predictors and two significant interactions were found: Internet use and income, and Internet use and employment status. In the case of income, Internet use appears to benefit older adults with regards to loneliness. Evidence of this was also found in the case of the interaction between Internet use and employment, although an interesting finding was that non-users who were employed actually had a negative loneliness trajectory (in stark contrast to all other groups), suggesting that while Internet use plays a role in predicting loneliness, being employed also significantly affects loneliness and may be a huge benefit for those who choose not to use the Internet or are unable.

In the case of personal growth, all demographic measures were found to significantly predict the outcome (although in the final regression model Internet use still retained a significant relationship with personal growth). For purpose in life, significant demographic predictors included age, education (but only for the 2010 sample), race, self-rated health, functional limitations, and previous levels of purpose in life. Internet use retained a significant relationship with the predictor only in the 2012 sample; in the 2010 sample, Internet use was not significant in the final model.

Summary

Differences in analytic techniques unfortunately make it difficult to make a grand statement regarding the relationship between Internet use, social integration and support, and mental health/well-being. However, the empirical evidence presented in this study suggests that, as hypothesized, Internet use does have a significant effect on mental health/well-being. Social integration theory, as first outlined by Durkheim and applied within an ICT-framework by DiMaggio et al. (2001), predicts that Internet use would have a significant effect on social life to the extent that it would influence objective mental health and subjective mental well-being. The findings of this study support this notion but expand upon this notion by pointing out what particular aspects of social life play the most crucial role in the relationship between Internet use and mental health/well-being. The results are most interesting for depression and loneliness, as the measurement of these outcomes allowed for longitudinal investigation. For these outcomes, Internet use continuously predicted more favorable scores even when controlling for other demographic and social characteristics. In addition, aspects of social integration and social support were found to mediate this relationship, but only partially. Similar results were found for the other outcomes, however the use of cross-sectional methodology does not allow for statements suggesting change over time. Overall, it appears Internet use benefits older adults with regards to mental health/well-being through impacts on social life. Moderation tests in the longitudinal analyses also suggest that Internet use can help promote better mental health/well-being outcomes for more disadvantaged groups (e.g., those suffering from increased functional limitations).

Discussion and Implications

The evidence for the benefit of Internet use was strongest for depression and loneliness, as the analyses incorporated longitudinal data and analytic techniques; in addition, the results were remarkably consistent between models regardless of what controls, mediators, and moderators were included. For both of these outcomes, Internet users reported lower scores, indicating better overall mental health/well-being. Evidence was found to support the notion that social integration and social support played a role such that Internet use had an effect on factors of social life that, in turn, had an effect on the outcomes. However, of interest is the fact that the mediation that was found was only partial in nature. While Internet use appears to affect the social relationships of older adults (both in quantity and quality), which in turn affects mental health/well-being, *a direct effect of Internet use on the outcomes was also found when controlling for social integration/support*. Put another way, it appears Internet use affects depression and loneliness in older adults through another pathway that was not measured in this study. Considering the possibilities of using the Internet in seeking out health information and seeking out ways to manage/cope with mental health/well-being issues, it is possible that the *information* part of information and communication technologies also plays a role in determining mental health/well-being in addition to its effect on social life.

While the evidence was strongest for depression and loneliness, evidence was also found to suggest similar relationships with personal growth and purpose in life, as the cross-sectional analysis did provide results that suggested (a) Internet use significantly predicted the outcome, (b) social integration/support acted as mediators, and (c) there remained a direct effect of Internet use on the outcomes that suggests other pathways through which Internet use benefits the user. However, in the case of life satisfaction the cross-sectional analysis revealed that social integration and social support explained away the significance of Internet use on the outcome. There was no evidence of a direct effect of Internet use on life satisfaction when controlling for the mediators; thus, unlike the other four outcomes, it does not appear that the information-seeking capabilities of the Internet have a strong impact on life satisfaction.

As previously stated, the number of older adults using ICTs is quickly expanding (Fox et al. 2001; Pew Research Internet Project 2013). Previous literature investigating the potential effects of ICTs on older adult users reveal a positive benefit (for example, see Chen and Persson 2002), and the results of this study support these findings. The question thus arises: what do these findings suggest with regards to application? In other words, how can these results be used to benefit the older adult population? First and foremost, the results suggest that getting older adults online may provide an avenue to combat the negative mental health/well-being outcomes in old age. As discussed in Chapter 2, however, there are numerous older adults who are not online due to various aspects of what has come to be called the "digital divide." Applied researchers concerned with combating mental health/well-being may find it of importance to create projects that lessen the digital divide for older adults. This may include bringing low-cost ICTs to the market and providing low-cost or free ICT classes to teach older adults how to use the technology. Studies have shown that ICT interventions in older adult populations, even those who are most frail, can have a positive impact on measures such as loneliness (for example, see Cotten et al. 2013).

Should applied researchers begin conducting interventions teaching older adults how to best utilize the technology, another question arises: what should be taught, and what should be focused on in these ICT classes? Because this study finds that both social integration and social support mediate the relationship of Internet use on mental health/well-being, it would prove prudent for applied researchers to focus on the social aspects of the Internet, such as emailing and social networking. However, as previously stated, Internet use also retained a significant direct effect on some of the outcomes in this study even when controlling for the mediators, and thus applied researchers developing ICT interventions may also find it imperative to focus on other aspects of Internet use that could improve mental health/well-being (such as health-information seeking).

Limitations and Future Research

This study attempted to provide a broad, general look at the effects of ICT use on mental health/well-being specifically for older adults. While there were a number of interesting findings that supported previous literature while also building on it, there were a number of limitations to this study that future studies should attempt to address:

Operationalization of ICT Use – ICT use was operationalized using a general Internet use question. However, studies have shown that other aspects of ICT use (e.g., frequency of use, timing of use, what is done online, motivations to use) can be more important predictors than simple "do you or don't you" ICT variables (for example, see Cotten 2008). While the HRS does collect data on other aspects of ICT use, it is collected in off-time surveys and thus could not be adequately linked to the mediators and outcomes. Future studies should attempt to investigate other operationalizations of ICT use, including frequency of use, types of activities done online, and what devices are used to access the Internet.

Operationalization of Mental Health/Well-Being – Despite incorporating a number of different conceptualizations of mental health and well-being, there are other possible operationalizations that were not available in the HRS dataset (e.g., mastery, self-acceptance). In addition, the emphasis was placed on mental health/well-being measures that did not include a clinical diagnosis. It is possible that the results could be different if focus was placed on such outcomes as clinically-diagnosed depression or anxiety.

Measurement of the Mediators - Another limitation associated with the investigation is the measurement of social integration and social support. While social integration, when compared to social support, is often referred to as the quantity of social ties rather than the quality of social ties, there is no consensus among researchers as to how social integration should be measured. Construction of a social integration index is typically difficult as various factors tend not to load on one another; as an example, while visiting friends and visiting family can be considered aspects of social integration, a high score for one does not necessarily mean a high score for the other is assured. For this investigation, social integration was operationalized in multiple ways in order to get a more complete picture of what role social integration plays in the relationship between ICT use and mental health/well-being; however there may be more adequate measures of social integration. In addition, while social support is operationalized using a reliable and valid scale, it is a scale that focuses on positive aspects of support; however, social support can also be negative, and future research should investigate whether ICT use has any relationship with negative support as well as positive support.

Cross-Sectional Analysis – As previously mentioned, longitudinal analysis could not be performed for three of the five outcomes. While cross-sectional analysis does provide evidence of association for life satisfaction, personal growth, and purpose in life, causation can only be inferred and not proven. As more waves of HRS data become available, it may be possible to re-run the analyses using longitudinal data so that the results may mirror what was found for depression and loneliness.

Use of Individual Growth Curve Modeling – Growth curve modeling is advantageous in longitudinal analysis due to its ability to account for within-person and between-person variation as well as its ability to adequately incorporate individuals with missing data. However, a limitation of individual growth curves is that while multiple time points are used to measure the variables, in the analysis the predictors and outcomes are examined *within the same time point*. Put another way, in the depression analysis Internet use in 2004 was examined as a predictor of depression in 2004, use in 2006 was examined as a predictor of depression in 2006, etc. This type of modeling does allow for the construction of outcome trajectories, however when measuring *effect* of predictors it is assumed that the effect of the predictor is occurring within the same time point that the outcome is measured. There is no measurement of a lagged effect despite the fact that a lagged effect could be possible. As an example, while Internet use in 2004 was examined as a predictor of depression in 2004, it could be that Internet use in 2004 has a lagged effect on depression and that the effect of Internet use wouldn't show up until the 2006 survey or later. Other longitudinal models, such as autoregressive models, can account for lagged effects, and future research could determine what the timing is on the Internet's effect on mental health/well-being.

In addition to what was previously stated, future research should also focus on the best practices applied researchers can implement in decreasing the digital divide among older adults. This can include identifying specific populations that are at most risk for not having access to ICTs or those at most risk for not being able to adequately use the technology on their own. Finally, future research should also investigate the teaching methods that may best be used to help older adults master the technology in such a way to promote better mental health/well-being outcomes.

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APPENDIX

The research presented in this dissertation was approved by the Institutional Review Board (IRB) for Human Use at the University of Alabama at Birmingham on August 7th, 2013. The project was designated as Non-Human Subjects Research, Protocol #N130807001. The following page contains a copy of the IRB approval form.

THE UNIVERSITY OF
ALABAMA AT BIRMINGHAM

Institutional Review Board for Human Use

DATE: August 7, 2013

MEMORANDUM

TO: Ronald W Berkowsky
Principal Investigator

FROM: Cari Oliver, CIP
Assistant Director
Office of the Institutional Review Board (OIRB)

RE: Request for Determination—Human Subjects Research
IRB Protocol #N130807001 – Internet Use and Mental Health \ Well – Being in Old Age: Exploring the Roles of Social Integration and Social Support

A member of the Office of the IRB has reviewed your Application for Not Human Subjects Research Designation for above referenced proposal.

The reviewer has determined that this proposal is **not** subject to FDA regulations and is **not** Human Subjects Research. Note that any changes to the project should be resubmitted to the Office of the IRB for determination.

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