SOCIAL ISOLATION ACROSS THE ADULT LIFE SPAN: VARIATIONS BY GENDER

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ABSTRACT

Kaitlin Shartle: Social Isolation Across the Adult Life Span: Variations by Gender
(Under the direction of Robert A. Hummer)

This dissertation uses two nationally representative surveys which span from young adulthood to late life to examine social isolation across the adult life course in the United States. In the first chapter of this dissertation, I examine patterns and trends of social isolation by age, period, cohort, and gender by conducting descriptive analyses using the National Survey of Midlife Development in the United States (MIDUS) and the Health and Retirement Study (HRS). I find that about 14 percent of U.S. adults aged 25 and older are socially isolated with this percentage growing with advancing age as well as across period-based time. Additionally, there are gender differences in social isolation which vary based on whether relationship status is included or excluded from the measure of social isolation.

In the second chapter, I investigate the trajectory of social isolation across the adult life course and examine how social isolation varies by cohort and gender. This is done by testing five longitudinal models of social isolation: enduring, spontaneous, lagged effects, life course, and hybrid, using both MIDUS and HRS. This chapter shows that social isolation is relatively stable within people as they age through adulthood, which is due to both time-invariant factors and recent history. More recent birth cohorts have higher levels of social isolation. Additionally,

while men are more isolated than women earlier in adulthood, these disparities converge before reversing at later ages.

My third chapter examines the relationship between social isolation and self-rated health across adulthood and how this relationship differs by gender, again using MIDUS and HRS. This chapter demonstrates that social isolation and self-rated health influence each other in older adulthood, but not in early adulthood or midlife. There are few gender differences in the relationship between social isolation and self-rated health across adulthood, except that women in older adulthood may experience greater health risks to being socially isolated than men.

In sum, this dissertation advances understanding of social isolation across the adult life course in the United States by evaluating trends within and between-individuals across time, examining connections between social isolation and health, and assessing gender differences.

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LIST OF ABBREVIATIONS

Add Health	National Longitudinal Study of Adolescent to Adult Health
ALT	Autoregressive Latent Trajectory
AR	Autoregressive
BIC	Bayesian Information Criterion
BSNI	Berkman-Syme Social Network Index
CFI	Comparative Fit Index
DF	Degrees of Freedom
FIML	Full Information Maximum Likelihood
HPA	Hypothalamic-Pituitary-Adrenal
HRS	Health and Retirement Study
MAR	Missing at Random
MCAR	Missing Completely at Random
MIDUS	National Survey of Midlife Development in the United States
RMSEA	Root Mean Square Error of Approximation
SAQ	Self-Administered Questionnaire
SI	Social Isolation
SNS	Sympathetic Nervous System
SRH	Self-Rated Health
TLI	Tucker Lewis Index

INTRODUCTION

Social relationships are essential for survival. A large body of research shows that those who are more socially connected live longer and healthier lives than those who are less connected (Berkman and Syme 1979; Holt-Lunstad 2022; Holt-Lunstad, Smith, and Layton 2010; House, Landis, and Umberson 1988; Snyder-Mackler et al. 2020). While social relationships are comprised of many different structural, functional, and qualitative aspects (Holt-Lunstad 2018, 2022), social isolation has emerged as a critical determinant of health, particularly given the COVID-19 pandemic (Holt-Lunstad and Perissinotto 2023; National Academies of Sciences, Engineering, and Medicine 2020). The quantity of social relationships provides a structural foundation on which other aspects of social relationships, such as the quality of relationships, can build (Holt-Lunstad and Steptoe 2022). If this foundation is weak because of a lack of social connections, termed social isolation, then there is little opportunity for other aspects of social relationships to positively impact health and well-being.

The concept of social isolation has been defined in a multitude of ways in the research literature. For the purpose of this dissertation, I use the definition of social isolation from the National Academies of Science, Engineering, and Medicine (2020) report on social isolation and loneliness in older adults. It defines social isolation as the "objective lack of (or limited) social contact with others" (National Academies of Sciences, Engineering, and Medicine 2020:3). This definition was developed and agreed upon by the numerous scholars involved in the report, as well as by other researchers in the field (Holt-Lunstad et al. 2010; de Jong Gierveld and Hagestad 2006; Umberson and Montez 2010). By defining social isolation as the objective lack of social connections, it separates the concept of social isolation from loneliness, which is perceived social isolation. Although social isolation and loneliness are closely related, research has shown that these are two distinct concepts that should be measured separately (Cornwell and Waite 2009b; Coyle and Dugan 2012; National Academies of Sciences, Engineering, and Medicine 2020).

Social isolation is common in the United States, with research estimating that about 10-25 percent of older adults report being socially isolated or lonely (Adler 2019; Cudjoe et al. 2020; DiJulio, Muñana, and Brodie 2018). These estimates are disconcerting given that social isolation has been associated with a range of physical health outcomes, including premature mortality, accelerated cognitive decline, cardiovascular disease, and higher allostatic load (Barnes et al. 2022; Cacioppo and Hawkley 2003; Cené et al. 2022; Holt-Lunstad 2022; Holt-Lunstad et al. 2010; Shankar et al. 2013; Umberson, Crosnoe, and Reczek 2010). Social isolation not only affects the health and well-being of those who are isolated, but also the economy. Estimates suggest that social isolation among older adults is associated with $6.7 billion in annual Medicare spending (Flowers et al. 2017; Shaw et al. 2017).

Despite the substantial societal and health costs of social isolation, this issue has received little attention until the past few years. Important news outlets, such as the New York Times, have recently featured articles on social isolation and loneliness (Abelson 2021; Bakalar 2020; Friedman 2020; Inada 2021). Additionally, organizations such as the AARP Foundation, Kaiser Family Foundation, and Cigna have released reports on the health effects of social isolation; many of them consider social connectedness to be an organizational priority (Anderson and Thayer 2018; Cigna 2020; DiJulio et al. 2018). The increased attention to social isolation and loneliness has not only occurred in the United States but also internationally. Cross-national analyses have found that 22 percent of adults in the United States, 23 percent in the United Kingdom, and 9 percent in Japan reported being socially isolated or lonely (DiJulio et al. 2018). While the United Kingdom and Japan have each created the position of Minister of Loneliness to develop policies for both measuring and reducing loneliness, the United States has yet to develop a national coordinated approach to address social isolation (Inada 2021; Yeginsu 2018).

Attention to social isolation as a public health risk further increased dramatically during the COVID-19 pandemic. With most of the world under stay-at-home orders at some point during the pandemic, many people experienced an increase in social isolation (Kovacs et al. 2021; Peng and Roth 2022; Quintana et al. 2021). Research reports that 62 percent of adults felt socially isolated sometimes to very often during the pandemic (Birditt et al. 2021). Further research across 101 countries found that 13 percent of people reported a substantial increase in social isolation during the pandemic (O'Sullivan et al. 2021). The pandemic has also brought to light the weaknesses of U.S. social support systems; as a result, there have been calls for local and federal policies to address this public health crisis (Holt-Lunstad 2020b). The National Institute on Aging had put out a call for research on the health impacts of social isolation and loneliness during the pandemic (Necka 2021) and the U.S. Surgeon General has stated the importance of developing a national, coordinated approach to address social isolation and loneliness (Murthy 2021). Clearly, it is important for researchers to better understand the association between social isolation and health so that policies and interventions can have the greatest impact (Holt-Lunstad 2020b; National Academies of Sciences, Engineering, and Medicine 2020; Panchal et al. 2020; Smith 2019).

Although three decades of research has established that social isolation is associated with worse health, there is still a lot that is unresolved or unknown in this area (Cacioppo and

Hawkley 2003; Holt-Lunstad et al. 2010; House et al. 1988). First, there are still gaps in our understanding of the patterns and trends of social isolation among U.S. adults, particularly by age, period, birth cohort, and gender. To advance research on social isolation, it is important to first estimate the current prevalence, document changes in prevalence across recent years and birth cohorts, and document differences in social isolation across population subgroups. This documentation would allow researchers and stakeholders to better understand the scope of the issue in the United States. By examining trends in social isolation across multiple dimensions of time and for different population groups, this could help forecast the burden of social isolation. It is particularly important to examine social isolation in young adulthood and midlife to better understand trends over the adult life course. In short, a more extensive descriptive analysis of social isolation can provide foundational information on which to build.

Second, while research has examined trajectories of social isolation by age (Luo and Li 2022; Petersen et al. 2016; Umberson, Lin, and Cha 2022), there is no literature that explicitly determines the best fitting longitudinal model of social isolation. For example, is social isolation largely dependent on isolation at a younger age? Is there an increase in social isolation with age? Or is social isolation relatively stable within people as they age? This evidence will allow researchers to have a better understanding of how sticky or malleable social isolation is within individuals as they age. Additionally, it is important to investigate cohort and gender differences in social isolation. This could help identify at-risk groups and determine whether risks vary by age.

Third, literature examining the connection between social isolation and health is mostly limited to older populations. Since social isolation and health unfold together over the life course, it is important for research to examine a larger span of the life course to better understand their connection (Elder, Johnson, and Crosnoe 2003; Teas, Marceau, and Friedman 2023; Umberson et al. 2010). Similarly, research has primarily focused on how social isolation is linked to health and not on the reciprocal relationship between these two concepts. Ignoring the reciprocal relationship between social isolation and health does not fully capture how these concepts are related to each other.

Overall, this dissertation aims to address these gaps in the literature by investigating social isolation in the United States. This is particularly important because policies in this area are beginning to develop in response to the failings of our current support systems that were brought to light during the COVID-19 pandemic. The remainder of this dissertation is organized as follows. In my first chapter, I establish the conceptualization and measurement of social isolation, which I use across all three chapters. Next, I review the literature on the prevalence of social isolation, summarize debates on contested findings, and highlight gaps. I then provide descriptive analyses on the trends and patterns of social isolation in U.S. adults overall, as well as by age, period, cohort, and gender. I use two nationally representative datasets – the National Survey of Midlife Development in the United States (MIDUS) and the Health and Retirement Study (HRS) – to produce this descriptive work. In my second chapter, I review hypothesized longitudinal models of social isolation. I then test these longitudinal models, using both MIDUS and HRS, to determine the model specification that best fits the longitudinal trajectory of social isolation. Furthermore, I examine how social isolation varies by cohort and gender. In my third chapter, I review the literature connecting social isolation and self-rated health across the adult life course. I then examine the association between social isolation and self-rated health across the adult life course using the best fitting longitudinal model from the previous chapter and by investigating gender differences. I finish with some concluding thoughts on the implications of this work and future directions.

CHAPTER ONE. TRENDS AND PATTERNS OF SOCIAL ISOLATION ACROSS ADULTHOOD: GENDER DIFFERENCES IN THE UNITED STATES

Social isolation, or the objective lack of social contact with others, is a public health issue with damaging consequences for population health and the health care system (Flowers et al. 2017; Holt-Lunstad and Perissinotto 2023; Holt-Lunstad et al. 2010; Umberson et al. 2010). Previous literature has found that social isolation leads to worse health, including the development of chronic conditions (Cantarero-Prieto, Pascual-Sáez, and Blázquez-Fernández 2018; Cené et al. 2022; Holt-Lunstad 2022; Steptoe et al. 2013; Umberson et al. 2010). Poor health can limit quality of life and cost the medical system billions of dollars (Flowers et al. 2017; Shaw et al. 2017). The COVID-19 pandemic has exacerbated social isolation, putting this issue in the spotlight. Despite the increased attention given to social isolation in the research literature and media, there are still gaps in our understanding of the patterns and trends of social isolation in U.S. adults, particularly by age, period, birth cohort, and gender.

To advance research on social isolation and develop meaningful interventions, it is important to first estimate the prevalence of social isolation. This would allow researchers, policymakers, and others to understand the scope of the problem and assess future burden. While previous research has reported that 25 percent of older adults in the United States are socially isolated (Adler 2019; Cudjoe et al. 2020; DiJulio et al. 2018), these estimates mix reports of social isolation and loneliness, and do not include earlier years in the adult life course, such as midlife. Prevalence estimates of social isolation in Europe suggest that there is an age-gradient in social isolation, whereby isolation increases as individuals get older

(Hämmig 2019; Röhr et al. 2021). While studies using data from the United States find this age-gradient in late life, it is little research on whether pattern extends to earlier ages. Examining social isolation across a broader range of ages would provide key information on the prevalence of social isolation in U.S. adults.

In addition to age gradients in social isolation, there may also be differences in social isolation across periods of time. Some research suggests social isolation is increasing in more recent years due to declines in social capital and the increasing use of technology (Kannan and Veazie 2023; McPherson, Smith-Lovin, and Brashears 2006; Parigi and Henson 2014; Putnam 2000). Alternatively, studies by Fischer (2009, 2011) and others (Marsden and Srivastava 2012; Paik and Sanchagrin 2013; Pew Research Center 2009; Wang and Wellman 2010) find that levels of isolation have remained stable and resilient to societal changes. Evidence of period differences in social isolation would suggest that historical circumstances are playing a role in the prevalence of social isolation.

Age and period factors may be interacting to create differences in social isolation across birth cohorts. Research ignoring birth cohorts assumes that social isolation changes with age similarly for all birth cohorts. However, this may not be a reasonable assumption given the large societal changes, including economics, telecommunication, value of individualism, and the rise of the internet, within the past half century (Rainie and Wellman 2012). Cohort variations would emphasize the intersection of individual experiences and macrosocial influences in social isolation.

Age, period, and cohort differences in social isolation may also be conditioned by gender. Gendered systems have the potential to impact the development and structure of social networks, which can affect social isolation (Berkman et al. 2000). Evidence for gender differences in social isolation has been inconsistent, which could be due to factors such as the stage of life course examined and the measurement of social isolation (Cornwell, Laumann, and Schumm 2008; Cudjoe et al. 2020; Naito et al. 2021; Röhr et al. 2021; Steptoe et al. 2013; Umberson et al. 2022; Vandervoort 2000). Further analyses using a wide range of ages and different measurement strategies could provide additional insights into the discrepancies in the literature. Additionally, there is a dearth of literature examining how gender disparities in social isolation differ by age, period and/or cohort. These investigations could improve understanding of gender disparities.

In sum, the patterns and trends of social isolation among U.S. adults warrants further investigation. An extensive descriptive analysis of social isolation can help provide a foundation of information that helps with the investigation of more complex research questions. This chapter aims to fill gaps in previous literature by discussing the conceptualization and measurement of social isolation as well as estimating the prevalence of social isolation by age, period, birth cohort, and gender. To investigate these aims, I use two nationally representative datasets that span from young to late adulthood.

BACKGROUND

What is Social Isolation?

Durkheim's (1951) research on suicide spurred the development of early theories on social isolation, which were enhanced in the network analysis literature in the 1950s (Barnes 1954; Berkman et al. 2000). Durkheim and network theorists both view social connections as structural arrangements of social institutions which shape access to resources (Berkman et al. 2000). These theories suggest the consequences of social isolation largely stem from the lack of connection to social structures and institutions which can provide access to resources and in turn can shape behaviors and attitudes. Thus, the importance of social connections is not as much about passing or daily interpersonal conversations, but the larger lack of attachment to macro-social systems.

From this work and others, Berkman and colleagues (2000) developed a comprehensive framework to better understand how social relationships impact health by linking literature on upstream factors, such as contexts and structures of social relationships, with downstream factors, such as psychosocial mechanisms and biological pathways. Of particular importance to the conceptualization of social isolation is the assertion that social connections are part of larger social and cultural contexts which shape the structure of networks. Through this conceptualization, gendered systems can shape structures of social relationships, including social isolation. Additionally, in this conceptual model, psychosocial mechanisms such as social support, social influence, and access to resources mediate the relationship between structural aspects of social relationships and various outcomes. Thus, social connections provide a basis for which quality aspects of social relationships can build. Having a lack of social connections, i.e., social isolation, limits opportunities for these psychosocial mechanisms. Therefore, social isolation measures more upstream factors such as level of embeddedness rather than downstream mechanisms, such as social support.

Measurement of Social Isolation

In this dissertation, I use a modified version of the Berkman-Syme Social Network Index (BSNI) to assess social isolation. The BSNI measures social isolation by assessing the type, size, closeness, and frequency of contacts in a person's social network (Berkman and Syme 1979; Loucks et al. 2006). The index is a composite measure comprised of the number of social ties across four areas: marital status, number and frequency of contact with close friends and family, religious group membership, and membership in other community organizations. Each of the four measures is dichotomized and then summed to create a cumulative risk index ranging from zero to four. The dichotomous cutoffs signal low or infrequent contact or engagement with each type of social relationship.

The BSNI was originally developed as a test of the Boissevain model, which posits that social networks are comprised of multiple social ties that vary in terms of intimacy (Boissevain 1974). The four measures of the BSNI were chosen to reflect the spheres of interaction in the Boissevain model, including both intimate (marital status and friend/family contact) and weak ties (group participation and religious attendance), which can provide distinct types of support. For example, intimate, i.e. strong, ties can provide caring, concern, encouragement, and instrumental assistance such as financial aid or help with tasks (Thoits 2011). Meanwhile weak ties can provide information, advice, and validation of concerns (Granovetter 1973; Thoits 2011). Each type of social relationship in the index is given an equal weight to signify the importance of different types of support.

Initial analyses using the BSNI found that the risk of mortality was greater for individuals with higher values of the BSNI compared to any singular measure within the BSNI (Berkman and Breslow 1983). This suggests that there is a cumulative effect of social ties, where missing several types of social connections is associated with higher mortality risk. It is important to note that the specific type of social tie that is missing is not as important as how many types are missing. This is because one type of social tie can be substituted for another to reduce mortality risk. For example, people who are not married but have frequent contact with family and friends have similar mortality risk to those who are married but have infrequent contact with friends and family (Berkman and Breslow 1983). Mortality risk rises drastically when individuals have few or no social ties.

While a variety of instruments have been developed to measure social isolation, (Berkman and Syme 1979; Cornwell and Waite 2009a; Koenig et al. 1993; Lubben 1988), there is no standardized measurement approach. As such, I use the BSNI in this dissertation for several reasons. First, the BSNI has an underlying theoretical framework, which most other instruments do not have. As mentioned previously, the BSNI is an empirical test of the Boissevain model that assesses both strong and weak ties. These ties are comprised of four types of social relationships: marital status, number and frequency of contact with close friends and family, religious group membership, and membership in other community organizations.

Second, the BSNI is a frequently used measure of social isolation in population research (Loucks et al. 2006; Xiang et al. 2021a; Yang et al. 2013; Yang et al. 2016). Given the popularity of the BSNI, this index is replicable in most population health datasets. Additionally, the BSNI was recommended by a multi-disciplinary committee to be included in all electronic health records (Holt-Lunstad, Robles, and Sbarra 2017; Pantell et al. 2013). This index was chosen among other indices and domains of social connections because of its strong association with health as well as its usability in clinical and research settings. Third, the BSNI solely measures social isolation, while other instruments measure multiple concepts in the same index. For example, the Duke Social Network Index measures social support in addition to social isolation (Koenig et al. 1993).

Lastly, given the focus of previous research on social isolation in late life, some instruments have been developed specifically for older adults (Cornwell and Waite 2009a; Lubben 1988). With this dissertation focused on social isolation across adulthood, I need a measure of social isolation that was developed for a broader range of ages. The BSNI is validated for use in adults aged 18-64 (Berkman and Breslow 1983). While I analyze individuals above this age range, the BSNI presents the largest validated age range of any well-known measurement tool. Additionally, the BSNI's framework assesses the number of social ties, both strong and weak, across four types of social relationships; as such, it can be adapted to fit broader age ranges and datasets. A limitation of the BSNI is that social ties are dichotomized, limiting variation in the items. While this is a drawback, the dichotomization of social ties makes the BSNI more comparable across datasets.

Prevalence Estimates of Social Isolation

Estimates from the National Health and Aging Trends Study, AARP, and others prior to the COVID-19 pandemic suggest that approximately 25 percent, or 8 million, adults aged 50 and older are socially isolated (Adler 2019; Cudjoe et al. 2020; DiJulio et al. 2018). This percentage likely increased during the COVID-19 pandemic. In fact, a recent multi-country study of adults aged 18 and older by O'Sullivan et al. (2021) found that 13 percent of adults experienced a substantial increase in isolation during the pandemic. Similarly, Birditt et al. (2021) found that 62 percent of adults aged 18 to 97 in the United States reported feeling socially isolated sometimes to very often during the pandemic.

Although prior estimates of prevalence provide important information regarding trends in isolation, this research has primarily focused on older populations, particularly before the pandemic. While older adults may be at an increased risk of social isolation because they are more likely to live alone, experience the loss of family and friends, and have physical and cognitive limitations, social isolation may occur earlier in adulthood as well (Cornwell and Waite 2009b; Holt-Lunstad et al. 2010; National Academies of Sciences, Engineering, and Medicine 2020). Prior prevalence estimates may also be limited due to the study populations analyzed. For example, some studies only analyzed Medicare beneficiaries or a small age range of older adults (Adler 2019; Cudjoe et al. 2020).

Other studies that have examined the prevalence of social isolation across a wider span of the adult life course have primarily used European samples. A study conducted in Switzerland found that on average 8 percent of people aged 15 and older were socially isolated (Hämmig 2019). A similar study conducted in Germany by Röhr and colleagues (2021) found a slightly higher prevalence of social isolation, 12 percent. Estimating the prevalence of social isolation among U.S. adults allows researchers to better understand the scope of the issue, discover high-risk groups, and evaluate trends (National Academies of Sciences, Engineering, and Medicine 2020).

Variations in Social Isolation

Period Differences in Social Isolation

Period changes are variations over time that influence all age groups simultaneously (Yang and Land 2013). Periods can represent time periods, such as the Civil War, or calendar years. Changes over periods can be due to historical events or environmental factors such as wars, recessions, pandemics, or technological innovations. For example, breast cancer death rates decreased in the 2000s due to increases in the use of hormone replacement therapy (Yang and Land 2013). Evidence of period differences would suggest that historical circumstances are playing a role in the prevalence of social isolation.

Literature suggests that social isolation may be increasing in more recent years. Using the General Social Survey, McPherson and colleagues (2006) found that from the mid-1980s to mid-2000s, the number of people whom you can discuss important matters with had shrunk by one-third. In particular, family/friend contact and group membership showed large declines over the study period. Additionally, the authors found the number of people who had no one to talk to tripled. In a replication of this study, Pew Research Center (2009) found that the average size of Americans' networks had indeed shrunk by one-third, but the number of people who had no one to talk to only increased moderately. These patterns have also been found in more recent literature. For example, research on older adults has found that social isolation doubled from 2006/2008 to 2014 (Crowe et al. 2021). Additionally, Kannan and Veazie (2023) found an overall decline in social connectedness from 2003 to 2020 among people aged 15 and older.

The proposed increase in social isolation over time has been associated with modernization and the increasing use of technology (McPherson et al. 2006; Parigi and Henson 2014; Primack et al. 2017; Putnam 2000). First, the modernization approach suggests that modernity weakens bonds that connect people to their communities (Parigi and Henson 2014). This approach is linked to a Marxist framework which posits that capitalism produces atomization of relationships and alienation (Marx and Engels 1978). This approach is highlighted in the research by Putnam (2000) and McPherson and colleagues (2006) which suggest that people's networks and ties to their community are shrinking, creating a decline in social capital and weakening of trust. Second, researchers have posited that the increased use of technology is weakening our bonds with others and replacing intimate connections with more superficial ones (Misra et al. 2016; Turkle 2011). This research would suggest that:

Hypothesis 1a: Social isolation has increased from the 1990s to the 2010s.

However, other research posits that the increases in social isolation found in previous studies can be attributed to data artifacts. In particular, research by Fischer (2009) and Paik and Sanchagrin (2013) argues that the findings of shrinking networks found in McPherson et al. (2006) can be attributed to training effects and interview fatigue. For example, the network questions in the General Social Survey were placed in different parts of the interview in the years analyzed and the results did not match similar studies at the time. A similar study conducted in the General Social Survey using measures of informal participation, such as evenings spent with relatives, friends, neighbors, and going to a bar/tavern, found no declines in social connectedness from 1974 to 2008 (Marsden and Srivastava 2012). Additionally, a follow-up study by the Pew Research Center (2009) found that while social network size had shrunk by one-third, there were only small to modest changes in the number of people who reported they have no one to discuss important matters with. Furthermore, the Pew study (2009) observed that technological advances in communication have supplemented face-to-face contact and has led to a larger number of strong and weak ties than before such advancements. This research, as well as others, suggest that levels of isolation have remained stable and resilient to societal changes (Fischer 2009, 2011; Wang and Wellman 2010). Additionally, while recent literature suggests there is a decline in social connectedness (Kannan and Veazie 2023) data on social connectedness was based on in-person social engagement over the course of one day, which may not be representative of average social connectedness over a longer period of time.

Hypothesis 1b: Social isolation has remained stable from the 1990s to the 2010s.

Age Differences in Social Isolation

Life course research has long focused on the importance of age. The seminal piece by Riley (1987) posited that aging is a lifelong social process that can help elucidate the interplay between aging and social change. Chronological age has been associated with changes in many domains of life, including health, socioeconomic status, and family formation (Baker and Gamaldo 2022; Brown 2018; House, Lantz, and Herd 2005; O'Rand 2006; Umberson, Pudrovska, and Reczek 2010; Yang and Kozloski 2011). Examining age patterns of social isolation can provide key insights into who is at risk for social isolation. While previous research has found that social isolation is age patterned, the direction of this variation has been inconsistent in the literature.

Some research suggests that social isolation increases with age, particularly in late life, as older adults experience the death of family and friends; decrease participation in formal social roles, such as through retirement; and experience the onsets of chronic illnesses and impairments that limit their social interactions (Cudjoe et al. 2020; Hämmig 2019; Kannan and Veazie 2023; Marsden 1987; Marsden and Srivastava 2012; McPherson et al. 2006; Röhr et al. 2021). Similarly, research finds that older adults limit their social ties in later life (Charles and Carstensen 2010). This is supported by socioemotional selectivity theory which posits that older adults make selective reductions in their social networks to focus their time on maintaining close relationships (Carstensen 1993, 2021). In research based on European populations, Hämmig (2019) and Röhr et al. (2021) found evidence for an age-gradient in social isolation, with social isolation increasing as individuals age. For example, in Hämmig's (2019) study the author found that 7 percent of people aged 25-44 were considered socially isolated compared to 8 percent aged 45-64, and 12 percent aged 65 and older. Similarly, Röhr and colleagues (2021) estimated that 5 percent of people aged 18-39, 13 percent aged 40-49, 18 percent aged 50-59, 21 percent aged 60-69, and 22 percent aged 70-79 were socially isolated. These findings suggest:

Hypothesis 2a: Social isolation increases with age.

However, disparate research posits that isolation remains stable across the adult life course and may even decrease in late life (Ang 2019; Cornwell, Goldman, and Laumann 2021; Cornwell et al. 2008; Cornwell and Laumann 2015; Ertel, Glymour, and Berkman 2009). These differences are likely due to differences in measurement, the population assessed, and analytic strategy used. However, social isolation may remain stable with age for several substantive reasons. First, older adulthood is a key stage of the life course for adaptation and compensation (Kohli, Hank, and Künemund 2009; Parigi and Henson 2014). This is supported by continuity theory, which posits that middle-aged and older adults try to maintain existing social structures, such as social relationships, throughout their life span (Atchley 1989; Lynch et al. 2015). For example, research has found that following spousal bereavement, widows engage in higher levels of informal social participation, such as volunteering to maintain their social network (Donnelly and Hinterlong 2010; Li 2007; Utz et al. 2002). Similarly, while critical life transitions, such as retirement, may lead to decreases in some social relationship types, these transitions may also force older adults to become more socially connected in other areas to receive the support they need (Cornwell et al. 2008). Second, isolation may decrease in older adulthood as individuals engage in more informal social activities in their community and develop closer relationships with friends and family at the end of life (Ang 2019; Cornwell et al. 2008). These findings would suggest that:

Hypothesis 2b: Social isolation is stable or even decreases with age.

Cohort Differences in Social Isolation

Birth cohorts, individuals born within a similar time period, experience social and historical circumstances at the same ages (Ryder 1965). Cohorts are shaped by the historical times and places they experience over their lifetime and can reflect social change and accumulation of exposures over the life span (Elder 1998; Elder and Giele 2009; Elder et al. 2003). Differences in social and historical circumstances across cohorts can lead to divergent trends in social isolation. Examining these cohort trends could help forecast burden of social isolation. Similar to the literature on age patterns of social isolation, there are debates regarding birth cohort variations in social isolation.

Given large societal change, some research suggests that isolation is increasing in recent U.S. birth cohorts. For example, demographic trends show reductions in marriage rates and religious attendance as well as increases in childlessness in more recent cohorts (Cohn et al. 2011; Margolis and Verdery 2017; Schwadel 2011); all of which can contribute to isolation. Research by Putnam (2000) has largely been cited as support of the hypothesis that isolation is increasing among recent U.S. birth cohorts. Putnam argued in his book *Bowling Alone* (2000) that connections between individuals, including with family, friends, neighbors, and organizations, have drastically declined since 1970. These trends have largely been attributed to cohort effects, including the erosion of trust in institutions and increasing use of technology, among others (Parigi and Henson 2014).

Given this research, I hypothesize that:

> *Hypothesis 3a:* More recent birth cohorts have higher levels of social isolation than earlier birth cohorts.

While research by Putnam (2000) suggests that social isolation has increased in recent U.S. birth cohorts, others refute these findings (McDonald and Mair 2010; Paxton 1999). Lemann (2015) and Samuelson (1996) both claim that Putnam (2000) widely exaggerated declines in group participation. They find group participation has remained stable or experienced only modest declines across cohorts and periods. Lemann (2015) and Samuelson (1996) posit that these disparate findings are primarily due to the groups analyzed. While some groups have reduced membership due to shifts in economic, social, or political views, other groups have emerged in their place, leading to stable involvement in group activities across cohorts.

This research, as well as others, suggests that levels of isolation have remained stable across birth cohorts (Antonucci, Ajrouch, and Webster 2019; Fischer 2009, 2011; Marsden and Srivastava 2012; Wang and Wellman 2010). However, Antonucci and colleagues (2019) did find some variation in network structure and composition across cohorts reflecting social changes, including increased modes of communication and decreased number of children and siblings. This is similar to other research which argues that while more recent cohorts may maintain social connections in different ways, such as through greater use of electronic communication, the overall level of social connectedness has not changed across birth cohorts (Fischer 2011). While increased electronic communication may induce period changes, a technological advancement that influences all age groups, electronic communication has been used more widely by more recent cohorts (Vogels 2019). Research finds that more recent birth cohorts have higher levels of social connectedness than previous cohorts because technology has given more recent cohorts additional mediums to connect through and allows people to maintain long-distance contact with friends and family (Wang and Wellman 2010; Wellman, Boase, and Chen 2002).

Accordingly, I hypothesize:

> *Hypothesis 3b:* There are no differences in social isolation by birth cohort.

Gender Differences in Social Isolation

Social connections are conditioned by gender, which can impact the development and structure of social relationships for men and women (Berkman et al. 2000; Umberson et al. 2022). Gendered systems in the United States promote self-sufficiency, independence, and controlled emotion among men and interpersonal relationships and intimacy among women (Courtenay 2000; Erickson 2005; Umberson et al. 1996, 2014; Williams 2008). These upstream factors may affect men and women's social relationships and lead to gender differences in social isolation. Examining gender differences in social isolation can help identify at-risk population groups. Understanding gender differences in the prevalence of social isolation can also provide foundational descriptive information for further research, including investigating whether disparities in social isolation are contributing to gender disparities in other areas, such as health.

Evidence of gender differences in social isolation has been inconsistent. Some research has found that men are anywhere from 1.5 to four times more likely to be isolated than women, with this gap remaining after controlling for age and socioeconomic status (Cornwell et al. 2008; Cudjoe et al. 2020; Ejiri et al. 2018; Iliffe et al. 2007; Röhr et al. 2021; Vandervoort 2000). In addition to gendered structures which promote interpersonal relationships among women and independence among men, researchers have speculated that men are more isolated than women because women rely more heavily on multiple sources for support, while men mostly rely on their partners (Röhr et al. 2021; Taylor et al. 2000; Vandervoort 2000). Women have also been found to have closer relationships with friends and family (Chatters et al. 2018; Cornwell and Schafer 2016). Yet other research has found women to be more socially isolated and have steeper age trajectories of social isolation than men (Naito et al. 2021; National Academies of Sciences, Engineering, and Medicine 2020; Xiang et al. 2021). Others still have found no significant gender differences in social isolation (Kotwal et al. 2021; Shankar et al. 2011; Steptoe et al. 2013). These conflicting findings could be due to the ages, periods, and/or cohorts assessed as well as variations in the measurement of social isolation.

Although research has observed gender disparities in social isolation, most of this research is based on older adults. Of particular interest is whether gender disparities in social isolation vary across time, such as by age, period, and cohort. There is a dearth of literature examining the gender disparities in social isolation across periods. Gender disparities in social isolation across periods would suggest that historical events and/or environmental factors have affected men and women differently. For example, internet use was initially dominated by men, but became more evenly distributed among men and women in the 2000s (Fallows 2005). Women use the internet more often to connect with friends and family than men, while men are more likely to engage with interest groups online. Additionally, although marriage rates are declining for both men and women, they are declining more rapidly for women (United States Census Bureau 2020). While period changes may be occurring unequally for men and women, the disparities in these changes are likely modest. Instead, these changes may be more indicative of cohort trends, discussed below, as recent social and historical changes, such as the increased use of technology and changes in educational attainment trends, have gradually changed over time. Therefore, I hypothesize:

> *Hypothesis 4:* Gender disparities in social isolation have been stable from the 1990s to the 2010s.

A recent study by Umberson and colleagues (2022) provides key insights into gender disparities in social isolation by age. The authors find that men are more isolated than women in adolescence and young adulthood, with this disparity narrowing slightly until midlife. Around age 55, the trend diverges, with women becoming more isolated than men. Gender disparities in social isolation then continue to grow with advancing age. Yet other research finds that men become increasingly more isolated than women at older ages. For instance, Fischer and Beresford (2015) found that the gap in the frequency of contact with friends and family diverges between women and men in their 50s and 60s, with men becoming increasingly more isolated than women. This gap could be due to several reasons. First, women are more likely to have social ties outside of the workplace (Fischer and Beresford 2015; Moore 1990). Therefore, after retirement, men may become more isolated than women because men have fewer social ties outside of the workplace. Second, while community involvement increases after retirement, this increase is largely observed among women (Cornwell et al. 2008). Third, parenthood may increase social ties for women in a way that may not necessarily occur for men (McDonald and Mair 2010). While the direction of the gender gap in social isolation differs, both Umberson and colleagues (2022) and Fischer and Beresford (2015) suggest that the gender disparity in social isolation grows in older adulthood.

> *Hypothesis 5:* Gender disparities in social isolation widen with age, with men becoming more isolated than women.

In addition to examining whether men and women have different patterns of social isolation by age and period, it is also important to explore these trends by cohort. If risk factors for social isolation changed unevenly for men and women across cohorts, this would suggest that disparities in social isolation change across cohorts. The examination of cohort differences in social isolation is particularly important given the large social and economic changes that shaped the social conditions of women in the past century.

Women have experienced changes such as increased educational attainment, labor force participation, and more liberal attitudes to non-domestic labor for women in more recent cohorts (Cotter, Hermsen, and Vanneman 2011; Diprete and Buchmann 2006; Kim and Sakamoto 2017; Toossi 2002; U.S. Bureau of Labor Statistics 2021). Women have also experienced greater improvements in education than men. Given that low education has been found to be a risk factor for social isolation, greater improvements in education may have reduced isolation in women in more recent cohorts (Cudjoe et al. 2020; National Academies of Sciences, Engineering, and

Medicine 2020). Additionally, higher labor force participation for women and changes in attitudes toward gender roles may have led to greater access to different types of social relationships, including the expansion of social ties in formal roles, for women. Despite becoming more integrated in formal social ties, women are still expected to take on household and childcare duties, likely leading to similar levels of contact with family members compared to previous cohorts (Goldscheider, Bernhardt, and Lappegård 2015; Hochschild and Machung 2012; Reczek and Umberson 2016). While men have taken on more household duties than in the past, likely increasing ties to their family, these increases have been modest. The strain of balancing work and family life may lead to decreases in religious attendance and group meeting attendance for women in more recent cohorts. For example, women have had greater declines in religious attendance than men (Schwadel 2010). However, overall trends point to women having greater reductions in social isolation across cohorts than men. Thus, I hypothesize:

> *Hypothesis 6*: For women, the prevalence of social isolation has declined in more recent cohorts, while social isolation has remained stable across cohorts for men.

Gender disparities in social isolation may also vary by how social isolation is measured. In the article by Umberson and colleagues (2022), the authors find that the gender disparity in social isolation diverges in late adulthood, with women becoming more isolated than men. They posit that because women are more likely to be unmarried or widowed than men at this stage of the life course, and because marital status is a key dimension of social isolation, this leads to increasing isolation among women in late adulthood. Given the multitude of ways to measure social isolation, studies that include marital status as a dimension of isolation may produce different evidence of gender disparities than studies that do not include marital status. For example, Umberson and colleagues (2022) find that when including marital status in the social isolation index, women are more isolated than men in older adulthood. However, when taking marital status out of the social isolation index, men are more isolated than women in older adulthood. Thus, the inclusion or exclusion of marital status could lead to the inconsistent findings of gender differences in social isolation that are found in the literature. Overall, these findings suggest that:

> *Hypothesis 7:* When excluding marital status from the social isolation index, men will be more isolated than women across the adult life span.

PRESENT STUDY

This chapter aims to better understand the trends and patterns of social isolation among adults in the United States. This is accomplished through three research objectives. First, I estimate the prevalence of social isolation across the adult life span (ages 25 and above) in the United States. This expands current research on social isolation, which primarily focuses on older adult, European samples with individual measures of social isolation. Second, I investigate age, period, and cohort patterns of social isolation. By using two nationally representative datasets spanning multiple cohorts over most of the adult life course, I expand the understanding of age, period, and cohort patterns in social isolation. Third, I examine gender differences in social isolation. By assessing social isolation across the adult life span, across multiple birth cohorts, and by using different measurement strategies, I provide additional insights into the inconsistent literature on gender disparities.

DATA AND METHODS

Study Samples

To examine the prevalence of social isolation across adulthood in the United States I use data from the National Survey of Midlife Development in the United States (MIDUS) and the

Health and Retirement Study (HRS). Both datasets are representative of the U.S. population and include rich data on social relationships at different stages of the adult life course. MIDUS is a representative sample of English-speaking, non-institutionalized adults residing in the contiguous U.S (Brim, Ryff, and Kessler 2004). Participants were selected from four subsamples: a national random digit dialing sample, oversamples of five metropolitan areas in the U.S, siblings, and twin pairs. The first wave occurred between 1995-96 and included 7,108 adults aged 25 to 74. A follow-up was conducted 10 years later in 2004-06 comprising of 4,963 of the original 7,108 respondents aged 35-86 at the time. The most recent wave was conducted in 2013-14 with 3,294 respondents who were aged 44-93. I use all three waves in this analysis.

The HRS is a nationally representative bi-annual survey of more than 37,000 adults aged 50 and older, which began in 1992 and is ongoing (Sonnega et al. 2014). The initial HRS cohort consisted of individuals born between 1931-41. The Asset and Health Dynamics Among the Oldest Old (AHEAD) was conducted the next year to capture the 1890-1923 cohorts. In 1998, the two studies merged, and the 1924-30 and 1942-47 cohorts were added. HRS now replenishes the sample every 6 years with younger cohorts. Most recently, the 1960-65 cohort was added in the 2016 survey. Since some measures of social isolation were not effectively measured until the introduction of the Leave-Behind Questionnaire, which was used to assess psychosocial topics starting in 2006, I begin the HRS data analysis with the 2006 survey. The Leave-Behind Questionnaire was given to a random sample of one-half of households in the HRS in 2006, with the other one-half receiving the questionnaire in 2008, after which participants were given the Leave-Behind Questionnaire every four years. I pool data from 2006 and 2008, 2010 and 2012, and 2014 and 2016 to create full samples of HRS participants. While the 2020 data has been recently released, I do not include it in my analysis because the prevalence of social isolation likely increased during 2020 because of the COVID-19 pandemic. This could lead to erroneous conclusions about the prevalence and trajectory of social isolation given the 2020 data must be pooled with the 2018 data. Additionally, MIDUS did not interview participants during the pandemic.

Analytic Sample Size

The analytic sample includes respondents with valid weights and complete data on all measures of social isolation and covariates (age, birth cohort, and gender). I excluded 3,621 MIDUS respondents at Wave 1; 2,721 at Wave 2; and 1,880 at Wave 3 because of missing weights. Weights were only available for the national random digit dial sample of MIDUS, reducing the eligible sample. I further excluded MIDUS respondents who did not complete the self-administered questionnaire(s) (SAQ) after their phone interview. Given that three of the four items in the social isolation index (family and friend contact, religious attendance, and community involvement) were only administered in the SAQ, I excluded the 1,057 respondents who did not take the SAQ (453 at Wave 1; 447 at Wave 2; and 157 at Wave 3). After these exclusions, five percent of respondents were dropped due to item missingness. This led to an analytic sample of 2,929 at Wave 1; 1,732 at Wave 2; and 1,192 at Wave 3 of MIDUS. As for HRS, after excluding respondents with missing weight data, under two percent of respondents were dropped due to item missingness. This led to an analytic sample of 15,698 for the pooled 2006 and 2008 sample (which I term Wave 1); 19,252 for the pooled 2010 and 2012 sample (which I term Wave 2); and 18,094 for the pooled 2014 and 2016 sample (which I term Wave 3).

Measures

I use a modified version of the Berkman-Syme Social Network Index (Berkman and Syme 1979) to assess social isolation. Social isolation is measured using a cumulative index comprised of four types of social relationships: relationship status[1], frequency of contact with friends and family, religious group attendance, and community involvement. I combine group meeting participation, as used in the original BSNI, and volunteering together to create a more comprehensive measure of community involvement.

Table 1.1 displays the measurement of social isolation in MIDUS and HRS. Each type of social relationship was dichotomized and then were summed to create a risk index ranging from zero to four for each of the included waves of the two datasets, with higher scores indicating more isolation. My coding of the social isolation index is similar to other studies (Ford, Loucks, and Berkman 2006; Glei et al. 2012; Pantell et al. 2013; Yang et al. 2013). This coding not only makes my results comparable to other studies, but also makes the indices comparable across datasets and waves. Additionally, research suggests that missing multiple types of social relationships is what confers the most health risk, lending support to the cumulative risk coding (Berkman and Breslow 1983). To identify the prevalence of social isolation, I further categorized social isolation into a dichotomous variable, with those isolated in three or four types of social relationships considered to be highly isolated (Berkman and Syme 1979; Loucks et al. 2006). The following subsections describe how the four types of social relationships were measured in the respective datasets.

Measuring Social Isolation in MIDUS

In MIDUS, all measures in the cumulative risk index of social isolation were measured consistently across waves. First, relationship status was assessed as whether the respondent was married or cohabitating. Since the index was created to assess social isolation, those who were

[1] I use the term relationship status instead of marital status to better represent married and cohabitating relationships.

not married or cohabitating were coded as one while those who were married or cohabitating were coded as zero. Second, the family and friend contact measure was created as a combination of two separate questions. Family contact was assessed by asking "How often are you in contact with any members of your family—that is, any of your brothers, sisters, parents, or children who do not live with you—including visits, phone calls, letters, or electronic mail messages?" Similarly, friend contact was assessed by asking how often they talked—through visits, phone calls, letters, or electronic mail messages—to friends. Respondents who were in contact with family or friends less than once a week were coded as one while those who had contact with family or friends once a week or more were coded as zero. Third, religious attendance was coded to one if respondents did not attend any religious services in the past month and zero if they attended once a month or more. Lastly, a variable indicating community involvement was created using measures of group meeting participation and volunteering. Group meeting participation was assessed as a combination measure of frequency of attendance per month in sport/social, professional, and other group meetings. Volunteering was assessed as the average number of hours spent volunteering a month. Respondents were coded as one if they did not attend any group meetings or volunteer in the past month and zero if they attended at least one group meeting and/or volunteered in the past month.

Measuring Social Isolation in HRS

Each measure in the social isolation cumulative risk index was measured the same way across all used waves of the HRS, except community involvement. Relationship status and religious attendance were both asked and coded the same way as in MIDUS. As for family and friend contact, this measure is a combination of four measures assessing the frequency of contact in-person, by phone, or by mail per month with their mother, father, children, and friends. In each of the four measures respondents were coded as one if they had contact with that person(s) less than once a week and zero if they had contact with that person(s) once a week or more. Parents and children who live with the respondent were coded to be zero. Additionally, respondents whose parents were not alive or had no friends/children were coded as one. The family and friend contact measure was coded as one if the respondent had contact with parents, children or friends less than once a week and zero otherwise. Last, community involvement was assessed using a combination measure of group meeting participation and volunteering. Group meeting participation was measured as the frequency of participation per month in group meetings. In 2006, respondents were asked about their participation in meetings or programs of groups, clubs or organizations. In 2008 and every survey after, group meeting participation was split into two questions: participation in sport, social, and other meetings, and participation in non-religious organization meetings. In survey years 2008-2016, the total frequency of participation across the two questions were calculated. Volunteering was assessed by whether the respondent volunteered in the past year. Respondents were coded as zero if they didn't attend any group meetings in the past month or volunteered in the past year and one if they attended one or more meetings a month and/or volunteered in the past year.

Covariates

Covariates include age, cohort, and gender. All covariates were coded the same way across datasets and waves. Age was measured in years. Using birth years, I grouped respondents into six 10-year birth cohorts: 1915-24 (Jazz Age Babies), 1925-34 (Depression Kids), 1935-44 (War Babies), 1945-54 (Early Baby Boomers), 1955-1964 (Late Baby Boomers), and 1965-1974 (Generation X; Hughes et al. 2005; Yang and Lee 2009). HRS spans from Jazz Age Babies to the Late Baby Boomers, while MIDUS ranges from Depression Kids to Generation X. Lastly, gender was assessed with a dummy variable (0 = men, 1 = women). While measures in MIDUS and HRS are actually capturing sex rather than gender, I use terminology associated with gender in this dissertation. I frame variations in social isolation as differences due to gendered processes rather than biology; therefore, I use the term gender to better fit with this conceptualization.

Analytic Approach

Descriptive analyses were conducted in five steps. First, I estimated the cross-sectional prevalence of social isolation within each wave of MIDUS and HRS. I used Wald tests to test for significant differences in the prevalence of social isolation across waves to examine period variations. Second, I examined age differences in social isolation within and across each wave of the datasets. Third, I created age-by-cohort tabular arrays of the prevalence of social isolation, with 10-year age intervals defining the rows and 10-year birth cohorts defining the columns, to further examine age and cohort differences. To increase cell sizes when splitting the sample by age and cohort, I pool all three waves of data to create the tabular arrays. Chi-squared tests were used to assess age and cohort differences. Fourth, I assessed gender differences in social isolation by stratifying the analysis of cross-sectional prevalence, prevalence of social isolation by age, and age-by-cohort tabular arrays by gender. Last, to test the extent to which gender disparities in the prevalence of social isolation differ by relationship status, I analyzed the gender stratified descriptives excluding relationship status from the social isolation index, resulting in a three-item index, and compared them to the results including relationship status. All models adjust for complex survey design and are weighted using study-specific cross-sectional weights.

While it is important to study age, period, and cohort variations to better understand changes in social isolation, it is important to recognize the entanglement of these three factors. It is difficult to separate out age, period, and cohort variations, particularly in descriptive analyses, because of the exact linear dependency between age, period, and cohort, i.e., the identification problem. Therefore, it is important to note that my descriptive analyses cannot disentangle these sources of variation. However, descriptive analysis is helpful to examine observed trends and provide foundational information to build on in more complex analyses which can better address the identification problem.

RESULTS

Cross-Sectional Prevalence of Social Isolation

Tables 1.2A and 1.2B present the weighted cross-sectional prevalence of social isolation in MIDUS and HRS, respectively. It is important to keep in mind that MIDUS respondents are aging across survey years. While HRS respondents are also aging across survey years, the HRS sample refreshes every six years with the addition of a new six-year birth cohort. These differences in survey design make results from MIDUS and HRS difficult to compare to each other. The tables show that, on average, people have low levels of contact in one or two types of social relationships in the social isolation index (mean isolation of 1.27 in MIDUS and 1.46 in HRS), with about 12 percent of people in MIDUS and 17 percent in HRS considered highly isolated. When averaging across datasets and waves, this corresponds to about 14 percent of adults being highly isolated.

Low contact is highest for items indicating weak ties, religious attendance and community involvement, then strong ties, relationship status and family/friend contact. For example, around 40 to 50 percent of respondents in MIDUS and HRS have low levels of community involvement and 50 percent do not frequently attend religious services. Meanwhile, only 5 to 16 percent have low family and friend contact and 27 to 35 percent are not married or cohabitating.

Results also suggest there is a modest increase in social isolation in more recent survey years, lending moderate support for Hypothesis 1a over 1b. In MIDUS, the mean social isolation score increases from 1.25 (SD=0.95) at Wave 1 to 1.33 (SD=0.99) at Wave 3. Similar trends are observed in HRS, where social isolation increases from 1.42 (SD=1.08) at Wave 1 to 1.48 (SD=0.99) at Wave 3. The increase in social isolation across survey years is due to an increase in the proportion of respondents who are not married or cohabitating and who do not frequently attend religious services. While these results suggest that social isolation may be increasing in more recent years, it is important to remember that both MIDUS and HRS are longitudinal datasets. Therefore, age is confounded with survey years, thus making it difficult to determine whether the change in social isolation is due to period-related or age-related change. Further analysis is needed using more complex methods to disentangle these effects.

Age-Specific Prevalence of Social Isolation

Next, I examined the cross-sectional, age-specific prevalence of social isolation (Tables 1.3A and 1.3B). The MIDUS results show no significant increases in social isolation with age. However, findings suggest that there might be modest increases in social isolation with age, particularly in late life (ages 80+). For example, at Wave 2 of MIDUS, average isolation increases from 1.15 (SD=0.91) in young adulthood to 1.25 in midlife (SD=0.94) and older adulthood (SD=0.99) to 1.35 (SD=1.07) in late life, with the proportion highly isolated increasing from 8 percent to 15 percent across those life stages. Examining age differences among the individual types of social relationships, results indicate that the proportion of people who are not married or cohabitating increases with age, while those who do not regularly attend religious services declines with age. Meanwhile, there are few significant age differences in family and friend contacts and only modest increases in the proportion of people with low community involvement with age. These findings are similar across all three waves of MIDUS.

The HRS results show similar, but more distinct, differences in social isolation with age, especially for those in late life (Table 1.3B). In the HRS, average isolation increases from 1.36 (SD=0.86) in midlife to 1.76 (SD=1.25) in late life at Wave 1, from 1.43 (SD=0.97) to 1.84 (SD=1.25) at Wave 2, and 1.46 (SD=0.93) to 1.77 (SD=1.16) at Wave 3. From midlife to late life, the percentage of those who are highly isolated increases from about 15 percent to around 28 percent. Increases in social isolation with age result from increases in the proportion of people who are not married/cohabitating, have low family and friend contact, and have low community involvement. The increase in the percentage of those not married/cohabitating is particularly striking, doubling from around 30 percent to 60 percent from midlife to late life. At the same time, the proportion of people who do not regularly attend religious services drops. These results indicate support for Hypothesis 2a – that social isolation increases with age. Similar to the overall prevalence estimates presented above, the age-specific results also suggest modest increases in social isolation across survey years that occur for all age groups.

Age-by-Cohort Estimates of Social Isolation

Age-by-cohort tabular arrays of social isolation are presented in Tables 1.4A and 1.4B, which display mean social isolation, and Tables 1.5A and 1.5B, which display the proportion isolated. Each table uses data from all three waves of MIDUS or HRS. In MIDUS, I find significant differences in the mean level of social isolation by cohort. Results suggest that more recent cohorts are more isolated. For example, for respondents in their 50s, the average social isolation score is 1.25 (SD=0.98) for those born in the 1935-1944 cohort, 1.29 (SD=0.94) for those in the 1945-1954 cohort, and 1.36 (SD=0.99) for those in the 1955-1964 cohort. However, there are no significant cohort differences in the proportion socially isolated by cohort. Overall, this lends support to Hypothesis 3a, which suggests that more recent birth cohorts will have higher levels of social isolation than earlier born cohorts.

The HRS analysis shows significant cohort differences in the mean levels of isolation, as well as in the proportion isolated by birth cohort. However, unlike results from MIDUS which show consistent declines in isolation in more recent cohorts, the HRS results are mixed. While some results suggest that isolation declines in more recent cohorts, others suggest an increase, stability, or a changing pattern. For example, for respondents in their 60s, the average social isolation score is 1.40 (SD=1.09) for those born in the 1935-1944 cohort, 1.44 (SD=0.93) for those in the 1945-1954 cohort, and 1.36 (SD=0.84) for those in the 1955-1964 cohort.

Gender Differences in Social Isolation Across the Adult Life Span

To examine gender differences in social isolation, I stratify the previous analyses (cross-sectional prevalence, prevalence of social isolation by age, and age-by-cohort tabular arrays) by gender. Results from both MIDUS (Table 1.6A) and HRS (Table 1.6B) suggest that there are few overall gender differences in social isolation. One exception is that men are more isolated than women at Wave 1 of MIDUS (1.29 compared to 1.21) and women are more isolated than men at Wave 3 of HRS (1.45 compared to 1.50). There is also little evidence that gender disparities in social isolation change across survey years, which supports Hypothesis 4. However, as mentioned previously, it is difficult to disentangle age and period change due to the longitudinal design of both MIDUS and HRS.

Examining the four individual types of social relationships in the social isolation index, women have higher proportions of people not married/cohabitating, but men have higher proportions of low family/friend contact and low religious attendance. The gender disparity in the proportion not married/cohabitating is particularly wide. In MIDUS, 19 to 23 percent of men across all three waves are not married/cohabitating compared to 31 to 40 percent of women. Meanwhile, in the HRS, this disparity is even wider. While 21 to 26 percent of men across all three waves are not married/cohabitating, this percentage is twice as large (around 43 percent) for women. There are no gender differences for community involvement. These trends are comparable across datasets, with a slightly wider gender disparity in HRS.

Next, I examined social isolation stratified by both age and gender (Tables 1.7A and 1.7B). In MIDUS, there are minimal gender differences in mean social isolation with age, but results suggest that social isolation modestly declines for men and modestly increases for women with advancing age. For example, at Wave 2, mean social isolation decreases from 1.28 (SD=0.82) to 1.17 (SD=0.82) from young adulthood to late life for men and increases from 1.04 (SD=0.96) to 1.50 (SD=1.24) from young adulthood to late life for women. When looking at the four individual types of social relationships, the gender gap in the proportion of people with low religious attendance, with men not attending religious services as frequently, seems to narrow at older ages. The largest gender gaps occur in the proportion who are not married or cohabitating. The percent of men not married/cohabitating remains stable with age, around 20 percent. Meanwhile for women, the percent not married/cohabitating increases from around 25 percent in young adulthood to 30 percent in midlife to 50 percent in older adulthood, and 65 percent in late adulthood.

The HRS results indicate that while men are more isolated than women in midlife, this gap narrows in older adulthood and reverses in late life, with women becoming more isolated than men. For instance, at Wave 1, men have a mean isolation score of 1.40 (SD=0.33) during midlife compared to 1.33 (SD=0.89) for women at the same life stage. During older adulthood, men and women have the same mean social isolation score (1.36). However, the gender gap reverses in late life, resulting in men having lower mean isolation, 1.62 (SD=1.36), than women 1.84 (SD=1.18). These results mirror findings by Umberson and colleagues (2022). The diverging gender gap in late life is primarily due to large increases in the proportion of women who are not married/cohabitating compared to men. At Wave 1, 20 percent of men during midlife are not married/cohabitating compared to 32 percent of women at the same life stage. This gap continues to increase, with 19 percent of men and 46 percent of women not married/cohabitating in older adulthood, and 33 percent of men and 75 percent of women not married/cohabitating in late life. Thus, the gender disparity in the proportion not married/cohabitating more than doubles from midlife to older adulthood and almost quadruples from midlife to late life. These findings lend partial support for Hypothesis 5 – that gender disparities in social isolation widen with age. While disparities widen, this does not occur until late life.

Tables 1.8 and 1.9 display age-by-cohort tabular arrays stratified by gender in Wave 3 of HRS. Due to the small cell size in MIDUS that resulted after splitting the sample by age, cohort, and gender, sex-stratified age-by-cohort tabular arrays were only conducted in the HRS. Overall, there are minimal gender differences in the age-by-cohort tabular arrays, except that within cohorts women seem to have larger increases in social isolation with age than men. For example, in the 1935-1944 cohort, isolation decreased from 1.43 to 1.38 to 1.29 for men as they age from their 50s to 70s. Contrastingly, isolation increases from 1.45 to 1.46 to 1.54 at the same ages for women. There are only small cohort differences in social isolation by gender, which partially supports Hypothesis 6 – that social isolation remains stable across cohorts for men. However, I did not find that the prevalence of social isolation declines in more recent cohorts for women, as also hypothesized.

Variations in Gender Patterns of Social Isolation with the Inclusion or Exclusion of Relationship Status

To assess whether gendered patterns in social isolation differ with the inclusion or exclusion of relationship status, I ran analyses excluding relationship status from the social isolation index and compared the results to those with relationship status included in the index. Tables 1.10A and 1.10B display the cross-sectional prevalence of social isolation among men and women for both the 4-item index used previously and a 3-item index which excludes relationship status. Since the indices include a different number of items, the means cannot be directly compared; rather, differences in trends can be observed. Results show that when including relationship status in the social isolation index, there are minimal gender differences in social isolation. However, when excluding relationship status, results indicate that men are more isolated than women across all waves of MIDUS and HRS. These findings support Hypothesis 7 – that when excluding relationship status from the social isolation index, men are more isolated than women across the adult life span.

Further analyses in Tables 1.11A and 1.11B examine social isolation stratified by age and gender. The MIDUS results show that when including relationship status in the social isolation index, social isolation increases with age for women. However, when taking relationship status out of the index, social isolation remains stable or declines with age for women. Meanwhile the age-patterns for men are similar whether relationship status is included or excluded from the index. In the HRS, social isolation increases for both men and women in late life when including relationship status but decreases with age when excluding relationship status.

When comparing gender disparities in social isolation by age, the MIDUS and HRS results which include relationship status suggest that men are more isolated than women in young adulthood and midlife, but this gap narrows in older adulthood and reverses in late life. Contrastingly, when excluding relationship status from the index, men are more isolated than women at every age group, with this gender gap particularly pronounced in the HRS. For example, at Wave 3 of the HRS, men have a mean isolation score of 1.22 (SD=0.67) during midlife, 1.19 (SD=0.77) during older adulthood, and 1.16 (SD=0.92) during late life, compared to 1.19 (SD=0.72), 1.06 (SD=0.79), and 1.07 (SD=0.86) for women at the same life stages. This suggests that relationship status plays a significant role in the direction of gender differences in social isolation.

DISCUSSION

Social isolation is a critical determinant of health and well-being. The COVID-19 pandemic has brought attention to social isolation, leading to calls for local and federal policies to address this issue (Holt-Lunstad 2020b). Despite this increased attention, there are still gaps in our understanding of social isolation including how the prevalence of social isolation in the U.S. varies across time and different subgroups of the population. Those that have investigated this are primarily based on older adult, non-U.S. samples, with individual measures of social isolation, and has led to conflicting findings in the literature. This chapter aimed to better understand the patterns and trends of social isolation in U.S. adults by estimating the cross-sectional prevalence of social isolation by period, age, cohort, and gender in two nationally representative samples which span from young adulthood to late life.

I found that about 14 percent of U.S. adults aged 25 and older are considered highly isolated, with a higher percentage of adults isolated on weak ties (religious attendance and community involvement) than strong ties (relationship status and family/friend contact). These findings are lower than the 25 percent found in other studies (Anderson and Thayer 2018; DiJulio et al. 2018). However, these studies focused specifically on older adults, who have higher rates of isolation. The prevalence of social isolation found in this study is similar to the prevalence of 12 percent found among adults aged 18-79 in Germany (Röhr et al. 2021).

Examining social isolation by period, age, and cohort, I found modest increases in social isolation in more recent survey years, increases in social isolation with age, and evidence of cohort differences in isolation. The modest increases in social isolation in more recent survey years is consistent with literature by the Pew Research Center (2009) and Kannan and Veazie (2023). While previous literature has attributed period increases in social isolation to weakening bonds to communities and increased technology use, I do not find evidence for this explanation (McPherson et al. 2006; Parigi and Henson 2014; Putnam 2000). If increases in social isolation were due to weakening bonds to communities and close others, I would expect to see increases in the percentage of respondents with low family/friend contact and low community involvement, but do not find this in the data. Rather, increases in social isolation across periods are being driven by the percentage of respondents who are not married or cohabitating and who do not frequently attend religious services. Therefore, period variations in social isolation may be due to trends in marriage and religious attendance, which have been declining since the 1960s and 1980s, respectively (Cohn et al. 2011; Jones 2021). These results should be interpreted with caution given that variations across survey years are confounded with age effects. Despite this confounding, results indicate that increases in social isolation across survey years is modest and not as alarming as what has been posited by Putnam (2000) and others (McPherson et al. 2006).

This chapter also shows that social isolation increases with age, especially in late life; this is consistent with other studies (Cudjoe et al. 2020; Hämmig 2019; Kannan and Veazie 2023; Marsden 1987; McPherson et al. 2006; Röhr et al. 2021). The prevalence of isolation almost doubles from midlife (ages 40-64) to late life (ages 80 and older) in both MIDUS and HRS, which is due to increases in the percentage of people who are not married/cohabitating, have low family and friend contact, and have low community involvement with advancing age. Older adults are more likely than younger adults to experience the death of family and friends; have reduced participation in formal social roles, such as through retirement; and experience the onset of chronic illnesses and impairments, all which can limit their social interactions (Choi et al. 2018; Coyle, Steinman, and Chen 2017). Additionally, socioemotional selectivity theory suggests that older adults may actively prune their social networks to only maintain their close relationships (Carstensen 1993, 2021). Increases in the percentage of people not married/cohabitating with advancing age is particularly striking, doubling from mid- to late-life. Older adults are more likely to experience widowhood and divorce, likely driving these changes (Mayol-García, Gurrentz, and Kreider 2021).

I also found cohort differences in social isolation across birth cohorts. In MIDUS, more recent birth cohorts are more isolated than earlier born cohorts. However, in HRS the results are mixed. While findings indicate that levels of isolation differ by birth cohort in HRS, the direction of these findings is mixed. These mixed findings suggest that cohort differences in social isolation should be further explored using methods which can more effectively disentangle age, period, and cohort effects.

Gender stratified results indicate that there are gender disparities in social isolation by age, but not by survey years or across birth cohorts. I find that while men are more isolated than women in young adulthood and midlife, this gender gap narrows in older adulthood and reverses in late life, with women becoming more isolated than men. This divergent trend is primarily due to steep increases in the percentage of women not married or cohabitating with age that is not experienced to the same degree for men. These results mirror the findings by Umberson and colleagues (2022). The large increase in the percentage of women not married/cohabitating is because in late life women are more likely to be widowed than men (Mayol-García et al. 2021). However, when excluding relationship status from the social isolation index, men are more socially isolated than women overall and at every age group, similar to findings by Umberson et al. (2022). This indicates that relationship status plays a key role in gender differences in social isolation. The inclusion or exclusion of relationship status in the measurement of social isolation could have led to the inconsistent findings on the direction and magnitude of gender differences found in previous literature. It also suggests that mortality patterns may affect estimates of gender disparities in social isolation during late life.

Implications

Results from this chapter document the scope of social isolation among adults in the United States. Around 14 percent of U.S. adults aged 25 and older are highly isolated, which translates to over 27 million people. For comparison, around the same number of people in the U.S have diagnosed diabetes (Centers for Disease Control and Prevention 2020). The number of people who are socially isolated is likely to increase in the coming years due to the COVID-19 pandemic and the aging of the U.S. population (Holt-Lunstad and Perissinotto 2022; Holt-Lunstad et al. 2017; O'Sullivan, Burns, et al. 2021). These findings demonstrate the need to have policies and programs in place to address isolation. Examples include training service providers to identify people who are socially isolated, developing tools and resources to support those who are at risk, and offering referrals to existing local, state, and national programs that promote social connection (Allen et al. 2020; Holt-Lunstad 2020b). These policies and programs should focus on groups who are particularly at risk for social isolation, such as older adults.

This study suggests the need for future research in three key areas. First, while this chapter helps build a foundation of descriptive information on social isolation, further research should expand on these findings to develop more complex research questions. Some research has already begun to use more intricate methods to study social isolation. For example, Umberson and colleagues (2022) used growth curve models to assess age-related change in social isolation. However, a deeper investigation of trajectories of social isolation is needed, including analytic methods that can address the confounding of age, period, and cohort. This is an area I focus on in the next chapter.

Second, future work should continue to examine patterns of social isolation for other groups such as by race/ethnicity, socioeconomic status, geography, disability status, and in LGBTQ+ populations. This dissertation focuses on gender because it has the largest established evidence base to build from and because the datasets used in this study are not particularly diverse. Research on disparities in social isolation among various population sub-groups exists but more research is needed to assess trends and develop strategies to reduce isolation in these populations (Fredriksen-Goldsen et al. 2013; Naito et al. 2021; Taylor et al. 2022; Taylor, Chatters, and Taylor 2019).

Third, better measurement of social isolation that incorporates broader aspects of social connection and is applicable across a wider range of ages is needed. Digital communication, including social media and online communities, has changed the way many people connect with others. However, most population surveys do not assess digital communication beyond asking about communication via text messages. Population surveys also often do not ask about social connectedness in other domains, such as in the workplace. Additionally, the measurement of social isolation varies widely across studies and age groups. The creation of a singular measurement tool to assess social isolation can help address inconsistencies across studies. Additionally, a measure which is applicable and can be compared across age groups is needed to better understand patterns of social isolation across the life course.

Limitations

Although this study extends previous research by examining social isolation by age, period, cohort, and gender across two nationally representative datasets, this research is limited in a few ways. First, I use the Berkman-Syme Social Network Index (BSNI; Berkman and Breslow 1983), but many other instruments exist to measure social isolation. The wide variety of measurement tools makes it difficult to compare findings across studies. While I chose the BSNI because of its underlying theoretical framework, inclusion in most population health datasets, strong associations with health, usability in clinical and research settings, measurement of a singular concept, and validation across a large range of ages, the index is not without its limitations. For example, social ties are dichotomized in the BSNI, which limits variation in the items. Additionally, while the BSNI can be adapted to a wide range of ages, it is not validated for adults 65 and older. Other scales have been developed to assess social isolation in older adults which often include different sets of variables, such as the inclusion of the total number of friends and the exclusion of religious attendance. While the BSNI is limited in some areas, some of these limitations make the measurement of social isolation more comparable across datasets. Second, due to data limitations, I restrict my coding of gender to women and men. Future research should investigate gender differences in social isolation across multiple gender identities.

Third, there are several limitations to using MIDUS and the HRS. Using data from two surveys with different designs and age ranges means that the datasets are not directly comparable. Although the datasets used in this study cover a wide range of birth cohorts, the youngest cohort (1965-1974) was born about 50 years ago. This means that a majority of the sample did not experience the widespread use of digital communication technologies, such as smartphones and the internet, until later in life. Additionally, while this study focused on social isolation among adults aged 25 and over, gaps remain in investigating social isolation among adolescents and young adults. This is primarily due to the lack of longitudinal data investigating social isolation among this age group, and a lack of consistent measurement with other data sets.

Fourth, as stated previously, the descriptive analyses used in this study cannot disentangle age, period, and cohort effects because of the linear dependency of these dimensions of time. While I created age-by-cohort tabular arrays to help deal with the confounding of these variables, these methods do not completely resolve this issue. However, these descriptive analyses provide trends and foundational information to build on in more complex analyses which can better address the identification problem. Fifth, this analysis examines periods using survey years, which includes short follow-ups. Future research should investigate period differences in social isolation over a longer span of time. Lastly, the age distribution within the age groupings is not consistent across waves and datasets. In MIDUS, the mean age within each grouping increases as individuals age across the survey years. In HRS, the mean age stays relatively consistent due to the sample being refreshed, but the midlife age category is skewed towards the oldest ages in the range and the older adulthood category is skewed towards the youngest ages in the range.

Conclusion

In sum, this study investigates trends and patterns of social isolation across the adult life span by age, period, cohort, and gender. Results show that 14 percent of U.S. adults are highly isolated, with this percentage growing with advancing age as well as across period-based time. Additionally, I found that gender disparities in social isolation vary when including or excluding relationship status from the measure of social isolation. When including relationship status in the measure of social isolation, men are more isolated than women in young adulthood and midlife with this gap narrowing in older adulthood and reversing in late life. Contrastingly, when excluding relationship status from the index, men are more isolated than women at every age group. Given the rapid aging of the U.S. population, this study underscores the importance of increased awareness, stakeholder coordination, and policies and initiatives to help address social isolation for diverse populations across the life course.

TABLES AND FIGURES

Table 1.1. Measurement of social isolation in MIDUS and HRS

Variables	Coding
Social isolation index	Sum of 4 items
Highly isolated	1 = 3 or 4 on the social isolation index
Not married or cohabitating	1 = not married or cohabitating
Low family and friend contact	1 = talked to friends or family less than once a week
Low/no religious attendance	1 = attended religious services less than once a month
Low community involvement	1 = didn't attend any meetings or volunteer in the past month

Table 1.2A. Cross-sectional prevalence of social isolation among U.S. adults – MIDUS

	Wave 1 (1995-96)	Wave 2 (2004-06)	Wave 3 (2013-14)
Prevalence, mean (SD)	1.25 (0.95)	1.24 (0.97)	1.33 (0.99)[bc]
Highly isolated prevalence, proportion	0.11	0.10	0.13[c]
Not married or cohabitating	0.27	0.27	0.32[bc]
Low family and friend contact	0.07	0.06	0.06
Low/no religious attendance	0.50	0.50	0.52
Low community involvement	0.41	0.41	0.43
Age, mean (SD)	45.62 (13.45)	54.59 (12.68)[a]	61.61 (11.13)[bc]
N	2,929	1,732	1,192

Notes: a = <0.05 difference between Waves 1 and 2; b = <0.05 difference between Waves 1 and 3;

c = <0.05 difference between Wave 2 and 3

Age range for Wave 1 is 25-75; Wave 2: 35-86; Wave 3: 44-93

Table 1.2B. Cross-sectional prevalence of social isolation among U.S. adults – HRS

	Wave 1 (2006/08)	Wave 2 (2010/12)	Wave 3 (2014/16)
Prevalence, mean (SD)	1.42 (1.08)	1.49 (1.09)[a]	1.48 (0.99)[b]
Highly isolated prevalence, proportion	0.16	0.18[a]	0.17[c]
Not married or cohabitating	0.33	0.34	0.35[bc]
Low family and friend contact	0.12	0.16[a]	0.10[bc]
Low/no religious attendance	0.49	0.53[a]	0.54[bc]
Low community involvement	0.47	0.47	0.49[bc]
Age, mean (SD)	66.46 (10.42)	65.31 (10.43)[a]	66.17 (9.70)[c]
N	15,698	19,252	18,094

Notes: a = <0.05 difference between Waves 1 and 2; b = <0.05 difference between Waves 1 and 3;

c = <0.05 difference between Wave 2 and 3

Age range for all waves is 50 and older

Table 1.3A. Cross-sectional prevalence of social isolation by age among U.S. adults – MIDUS

	Wave 1 (1995-96)	Wave 2 (2004-06)	Wave 3 (2013-14)
Prevalence, mean (SD)			
25-39 (Young Adulthood)	1.29 (0.94)	1.15 (0.91)	-
40-64 (Midlife)	1.23 (1.03)	1.25 (0.94)	1.32 (0.89)
65-79 (Older Adulthood)	1.20 (0.84)	1.25 (0.99)	1.30 (1.05)
80+ (Late Life)	-	1.35 (1.07)	1.47 (0.97)
Highly isolated prevalence, proportion			
25-39 (Young Adulthood)	0.10	0.08	-
40-64 (Midlife)	0.11	0.09	0.12
65-79 (Older Adulthood)	0.11	0.10	0.13
80+ (Late Life)	-	0.15	0.16
Not married or cohabitating, proportion			
25-39 (Young Adulthood)	0.28	0.20[a]	-
40-64 (Midlife)	0.25[d]	0.25	0.28
65-79 (Older Adulthood)	0.34[g]	0.37[eg]	0.35[g]
80+ (Late Life)	-	0.46[fh]	0.50[hi]
Low family and friend contact, proportion			
25-39 (Young Adulthood)	0.05	0.04	-
40-64 (Midlife)	0.09[d]	0.07	0.04[b]
65-79 (Older Adulthood)	0.05[g]	0.04	0.09[cg]
80+ (Late Life)	-	0.09	0.06
Low/no religious attendance, proportion			
25-39 (Young Adulthood)	0.55	0.54	-
40-64 (Midlife)	0.50[d]	0.55[a]	0.56[b]
65-79 (Older Adulthood)	0.34[eg]	0.38[eg]	0.46[bcg]
80+ (Late Life)	-	0.30[fh]	0.41[h]
Low community involvement, proportion			
25-39 (Young Adulthood)	0.41	0.37	-
40-64 (Midlife)	0.40	0.39	0.44
65-79 (Older Adulthood)	0.47[h]	0.46[g]	0.40
80+ (Late Life)	-	0.51	0.50
N	2,929	1,732	1,192

Notes: a = <0.05 difference between Waves 1 and 2; b = <0.05 difference between Waves 1 and 3; c = <0.05 difference between Wave 2 and 3; d = <0.05 difference between young adulthood and midlife; e = <0.05 difference between young adulthood and older adulthood; f = <0.05 difference between young adulthood and late life; g = <0.05 difference between midlife and older adulthood; h = <0.05 difference between midlife and late life; i = <0.05 difference between older adulthood and late life

Age range for Wave 1 is 25-75; Wave 2: 35-86; Wave 3: 44-93

Table 1.3B. Cross-sectional prevalence of social isolation by age among U.S. adults – HRS

	Wave 1 (2006/08)	Wave 2 (2010/12)	Wave 3 (2014/16)
Prevalence, mean (SD)			
50-64 (Midlife)	1.36 (0.86)	1.43 (0.97)[a]	1.46 (0.93)[b]
65-79 (Older Adulthood)	1.36 (1.28)	1.47 (1.20)[a]	1.41 (1.01)[bc]
80+ (Late Life)	1.76 (1.25)[hi]	1.84 (1.25)[ahi]	1.77 (1.16)[chi]
Highly isolated prevalence, proportion			
50-64 (Midlife)	0.13	0.15[a]	0.16[b]
65-79 (Older Adulthood)	0.15	0.18[af]	0.15[c]
80+ (Late Life)	0.27[hi]	0.30[ahi]	0.26[chi]
Not married or cohabitating, proportion			
50-64 (Midlife)	0.26	0.29[a]	0.31[bc]
65-79 (Older Adulthood)	0.34[g]	0.34[g]	0.33
80+ (Late Life)	0.59[hi]	0.59[hi]	0.60[hi]
Low family and friend contact, proportion			
50-64 (Midlife)	0.10	0.13[a]	0.10[c]
65-79 (Older Adulthood)	0.13[g]	0.18[ag]	0.10$_{bc}$
80+ (Late Life)	0.19[hi]	0.23[ahi]	0.12[bc]
Low/no religious attendance, proportion			
50-64 (Midlife)	0.54	0.57[a]	0.58[b]
65-79 (Older Adulthood)	0.45[g]	0.48[ag]	0.50[bcg]
80+ (Late Life)	0.44[h]	0.45[h]	0.45[h]
Low community involvement, proportion			
50-64 (Midlife)	0.46	0.45	0.47[c]
65-79 (Older Adulthood)	0.45	0.47[a]	0.47[b]
80+ (Late Life)	0.54[hi]	0.57[ahi]	0.61[bchi]
N	15,698	19,252	18,094

Notes: a = <0.05 difference between Waves 1 and 2; b = <0.05 difference between Waves 1 and 3; c = <0.05 difference between Wave 2 and 3; d = <0.05 difference between young adulthood and midlife; e = <0.05 difference between young adulthood and older adulthood; f = <0.05 difference between young adulthood and late life; g = <0.05 difference between midlife and older adulthood; h = <0.05 difference between midlife and late life; i = <0.05 difference between older adulthood and late life

Age range for all waves is 50 and older

Table 1.4A. Mean social isolation index (0-4) by age and cohort - MIDUS, Waves 1-3 (1995-2014)

	Cohort				
Age Interval	1925-1934	1935-1944	1945-1954	1955-1964	1965-1974
30-39				1.24 (0.97)	1.17 (0.91)
40-49			1.22 (0.95)	1.23 (0.99)	1.28 (0.98)
50-59		1.25 (0.98)	1.29 (0.94)	1.36 (0.99)	
60-69	1.21 (0.95)	1.19 (0.95)	1.35 (0.97)		
70-79	1.24 (0.96)	1.32 (1.05)			
80-89	1.51 (1.01)				

age group differences: p = 0.41
cohort group differences: p = 0.01

Table 1.4B. Mean social isolation index (0-4) by age and cohort - HRS, Waves 1-3 (2006-2016)

	Cohort				
Age Interval	1915-1924	1925-1934	1935-1944	1945-1954	1955-1964
50-59				1.40 (0.90)	1.42 (0.94)
60-69			1.40 (1.09)	1.44 (0.93)	1.36 (0.84)
70-79		1.39 (1.30)	1.43 (1.22)	1.41 (0.84)	
80-89	1.79 (1.23)	1.68 (1.21)	1.43 (1.13)		

age group differences: p = <0.001
cohort group differences: p = <0.001

Table 1.5A. Proportion socially isolated by age and cohort - MIDUS, Waves 1-3 (1995-2014)

	Cohort				
Age Interval	1925-1934	1935-1944	1945-1954	1955-1964	1965-1974
30-39				0.09	0.08
40-49			0.10	0.10	0.13
50-59		0.12	0.11	0.13	
60-69	0.11	0.08	0.11		
70-79	0.11	0.16			
80-89	0.18				

age group differences: p = 0.15
cohort group differences: p = 0.85

Table 1.5B. Proportion socially isolated by age and cohort - HRS, Waves 1-3 (2006-2016)

	Cohort				
Age Interval	1915-1924	1925-1934	1935-1944	1945-1954	1955-1964
50-59				0.15	0.15
60-69			0.15	0.16	0.12
70-79		0.16	0.17	0.15	
80-89	0.28	0.24	0.15		

age group differences: p = <0.001
cohort group differences: p = <0.001

Table 1.6A. Cross-sectional prevalence of social isolation by gender among U.S. adults – MIDUS

	Wave 1 (1995-96)		Wave 2 (2004-06)		Wave 3 (2013-14)	
	Men	Women	Men	Women	Men	Women
Prevalence, mean (SD)	1.29 (0.97)	1.21 (0.94)[d]	1.25 (0.96)	1.24 (0.98)	1.35 (0.99)	1.31 (0.99)
Highly isolated prevalence, proportion	0.12	0.09	0.09[a]	0.10	0.12	0.13[b]
Not married or cohabitating	0.23	0.31[d]	0.19[a]	0.34[d]	0.23	0.40[bd]
Low family and friend contact	0.09	0.05[d]	0.07	0.05	0.08	0.04[d]
Low/no religious attendance	0.57	0.44[d]	0.57	0.45[d]	0.59	0.47[d]
Low community involvement	0.41	0.42	0.42	0.40	0.46	0.41
Age, mean (SD)	45.24 (13.32)	45.97 (13.56)	54.66 (12.58)[a]	54.53 (12.77)[a]	61.25 (10.95)[bc]	61.92 (11.26)[bc]
N	1,416	1,513	788	944	565	627

Notes: a = <0.05 difference between Waves 1 and 2; b = <0.05 difference between Waves 1 and 3;

c = <0.05 difference between Wave 2 and 3; d = <0.05 difference between men and women

Age range for Wave 1 is 25-75; Wave 2: 35-86; Wave 3: 44-93

Table 1.6B. Cross-sectional prevalence of social isolation by gender among U.S. adults - HRS

	Wave 1 (2006/08)		Wave 2 (2010/12)		Wave 3 (2014/16)	
	Men	Women	Men	Women	Men	Women
Prevalence, mean (SD)	1.41 (1.06)	1.42 (1.10)	1.50 (1.06)[a]	1.49 (1.10)[a]	1.45 (0.95)[c]	1.50 (1.03)[bd]
Highly isolated prevalence, proportion	0.15	0.16	0.18[a]	0.18[a]	0.15[c]	0.18[bd]
Not married or cohabitating	0.21	0.43[d]	0.25[a]	0.43[d]	0.26[b]	0.44[d]
Low family and friend contact	0.15	0.10[d]	0.19[a]	0.13[ad]	0.12[bc]	0.09[cd]
Low/no religious attendance	0.56	0.44[d]	0.58[a]	0.48[ad]	0.59[b]	0.49[bcd]
Low community involvement	0.49	0.45[d]	0.48	0.46	0.49	0.48[bc]
Age, mean (SD)	65.66 (9.63)	67.14 (11.03)[d]	64.60 (9.60)[a]	65.91 (11.10)[ad]	65.45 (8.84)[c]	66.78 (10.40)[cd]
N	6,633	9,065	8,290	10,962	7,669	10,425

Notes: a = <0.05 difference between Waves 1 and 2; b = <0.05 difference between Waves 1 and 3

c = <0.05 difference between Wave 2 and 3; d = <0.05 difference between men and women

Age range for all waves is 50 and older

Table 1.7A. Cross-sectional prevalence of social isolation by age and gender among U.S. adults – MIDUS

	Wave 1 (1995-96)		Wave 2 (2004-06)		Wave 3 (2013-14)	
	Men	Women	Men	Women	Men	Women
Prevalence, mean (SD)						
25-39 (Young Adulthood)	1.40 (0.95)	1.20 (0.93)[j]	1.28 (0.82)	1.04 (0.96)	-	-
40-64 (Midlife)	1.26 (1.05)[d]	1.20 (1.01)	1.27 (0.95)	1.24 (0.93)	1.37 (0.86)	1.28 (0.92)
65-79 (Older Adulthood)	1.08 (0.83)[eg]	1.29 (0.83)	1.17 (0.98)	1.31 (1.00)[e]	1.30 (1.07)[b]	1.30 (1.04)
80+ (Late Life)	-	-	1.17 (0.82)	1.50 (1.24)	1.38 (1.12)	1.54 (0.85)
Highly isolated prevalence, proportion						
25-39 (Young Adulthood)	0.13	0.08[j]	0.06	0.09	-	-
40-64 (Midlife)	0.12	0.10	0.10	0.10	0.11	0.12
65-79 (Older Adulthood)	0.07[eg]	0.14[j]	0.09	0.11	0.13[b]	0.13
80+ (Late Life)	-	-	0.03[h]	0.25[j]	0.16c	0.16
Not married or cohabitating, proportion						
25-39 (Young Adulthood)	0.29	0.28	0.14[a]	0.24	-	-
40-64 (Midlife)	0.19[d]	0.30[j]	0.19	0.30[j]	0.24	0.32[j]
65-79 (Older Adulthood)	0.20[e]	0.46eg[j]	0.20	0.50[egj]	0.21	0.47[gj]
80+ (Late Life)	-	-	0.29	0.60[fhj]	0.24	0.69[hij]
Low family and friend contact, proportion						
25-39 (Young Adulthood)	0.06	0.04	0.04	0.05	-	-
40-64 (Midlife)	0.12[e]	0.06[j]	0.08[a]	0.06	0.06[b]	0.03[b]
65-79 (Older Adulthood)	0.05[g]	0.05	0.05	0.04	0.12[bcg]	0.06
80+ (Late Life)	-	-	0.13	0.06	0.08	0.05
Low/no religious attendance, proportion						
25-39 (Young Adulthood)	0.62	0.49[j]	0.64	0.46[j]	-	-
40-64 (Midlife)	0.56[d]	0.45[j]	0.62[a]	0.49[j]	0.62	0.51[j]
65-79 (Older Adulthood)	0.40[eg]	0.29[eg]	0.44[eg]	0.33[egj]	0.55[bc]	0.39[gj]
80+ (Late Life)	-	-	0.23[fhi]	0.35	0.47[c]	0.37
Low community involvement, proportion						

25-39 (Young Adulthood)	0.42	0.40	0.47	0.29[j]	-	-
40-64 (Midlife)	0.40	0.40	0.38	0.40	0.46	0.42
65-79 (Older Adulthood)	0.44	0.49[eg]	0.49[g]	0.44[e]	0.42	0.38
80+ (Late Life)	-	-	0.52	0.50	0.60[i]	0.44
N	1,416	1,513	788	944	565	627

Notes: a = <0.05 difference between Waves 1 and 2; b = <0.05 difference between Waves 1 and 3; c = <0.05 difference between Wave 2 and 3; d = <0.05 difference between young adulthood and midlife; e = <0.05 difference between young adulthood and older adulthood; f = <0.05 difference between young adulthood and late life; g = <0.05 difference between midlife and older adulthood; h = <0.05 difference between midlife and late life; i = <0.05 difference between older adulthood and late life; j = <0.05 difference between men and women

Age range for Wave 1 is 25-75; Wave 2: 35-86; Wave 3: 44-93

Table 1.7B. Cross-sectional prevalence of social isolation by age and gender among U.S. adults – HRS

	Wave 1 (2006/08)		Wave 2 (2010/12)		Wave 3 (2014/16)	
	Men	Women	Men	Women	Men	Women
Prevalence, mean (SD)						
50-64 (Midlife)	1.40 (0.81)	1.33 (0.89)[j]	1.49 (0.95)[a]	1.38 (0.97)[aj]	1.48 (0.89)[b]	1.43 (0.96)[bc]
65-79 (Older Adulthood)	1.36 (1.29)	1.36 (1.27)	1.47 (1.17)[a]	1.48 (1.22)[ag]	1.37 (0.97)[cg]	1.44 (1.04)[bj]
80+ (Late Life)	1.62 (1.36)[hi]	1.84 (1.18)[hij]	1.65 (1.31)[hi]	1.96 (1.18)[ahij]	1.55 (1.18)[ci]	1.90 (1.12)[hij]
Highly isolated prevalence, proportion						
50-64 (Midlife)	0.14	0.13	0.17[a]	0.13[j]	0.16	0.16[bc]
65-79 (Older Adulthood)	0.14	0.15[g]	0.18[a]	0.19[ag]	0.13[cg]	0.17[cj]
80+ (Late Life)	0.24[hi]	0.29[hij]	0.24[hi]	0.34[ahij]	0.19[bci]	0.31[chij]
Not married or cohabitating, proportion						
50-64 (Midlife)	0.20	0.32[j]	0.25[a]	0.33[j]	0.27[bc]	0.35[bcj]
65-79 (Older Adulthood)	0.19	0.46[gj]	0.22[a]	0.45[gj]	0.21[g]	0.43[bcgj]
80+ (Late Life)	0.33[hi]	0.75[hij]	0.34[hi]	0.75[hij]	0.35[hi]	0.76[hij]
Low family and friend contact, proportion						
50-64 (Midlife)	0.12	0.08[j]	0.17[a]	0.10[aj]	0.11[c]	0.08[cj]
65-79 (Older Adulthood)	0.17[g]	0.09[j]	0.21[ag]	0.15[agj]	0.13[bc]	0.08[cj]
80+ (Late Life)	0.24[hi]	0.15[hij]	0.26[hi]	0.20[ahij]	0.12[bc]	0.11[bchi]
Low/no religious attendance, proportion						
50-64 (Midlife)	0.59	0.49[j]	0.61	0.52[aj]	0.62	0.54[bcj]
65-79 (Older Adulthood)	0.52[g]	0.39[gj]	0.56[ag]	0.42[agj]	0.56[bg]	0.45[bcj]
80+ (Late Life)	0.49[h]	0.42[hj]	0.50[hi]	0.42[hj]	0.49[hi]	0.42[hij]
Low community involvement, proportion						
50-64 (Midlife)	0.49	0.44[j]	0.46	0.43[j]	0.48	0.45
65-79 (Older Adulthood)	0.47	0.43[j]	0.48	0.45[a]	0.47	0.47[bc]
80+ (Late Life)	0.56[hi]	0.52[hi]	0.55[hi]	0.59[ahi]	0.59[chi]	0.62[bchi]
N	6,633	9,065	8,290	10,962	7,669	10,425

Notes: a = <0.05 difference between Waves 1 and 2; b = <0.05 difference between Waves 1 and 3; c = <0.05 difference between Wave 2 and 3; d = <0.05 difference between young adulthood and midlife; e = <0.05 difference between young adulthood and older adulthood; f = <0.05 difference between young adulthood and late life; g = <0.05 difference between midlife and older adulthood; h = <0.05 difference between midlife and late life; i = <0.05 difference between older adulthood and late life; j = <0.05 difference between men and women

Age range for all waves is 50 and older

Table 1.8A. Mean social isolation index (0-4) by age and cohort - HRS, Waves 1-3 (2006-2016): Men

	Cohort				
Age Interval	1915-1924	1925-1934	1935-1944	1945-1954	1955-1964
50-59				1.44 (0.87)	1.47 (0.91)
60-69			1.43 (1.02)	1.46 (0.90)	1.32 (0.75)
70-79		1.31 (1.33)	1.41 (1.21)	1.48 (0.81)	
80-89	1.66 (1.31)	1.52 (1.27)	1.29 (1.09)		

age group differences: p = <0.001

cohort group differences: p = <0.001

Table 1.8B. Mean social isolation index (0-4) by age and cohort - HRS, Waves 1-3 (2006-2016): Women

	Cohort				
Age Interval	1915-1924	1925-1934	1935-1944	1945-1954	1955-1964
50-59				1.35 (0.91)	1.37 (0.96)
60-69			1.37 (1.15)	1.43 (0.95)	1.40 (0.91)
70-79		1.45 (1.28)	1.45 (1.24)	1.34 (0.85)	
80-89	1.87 (1.17)	1.79 (1.15)	1.54 (1.14)		

age group differences: p = <0.001

cohort group differences: p = <0.001

Table 1.9A. Proportion socially isolated by age and cohort - HRS, Waves 1-3 (2006-2016): Men

	Cohort				
Age Interval	1915-1924	1925-1934	1935-1944	1945-1954	1955-1964
50-59				0.16	0.16
60-69			0.15	0.16	0.08
70-79		0.14	0.16	0.18	
80-89	0.24	0.20	0.10		

age group differences: p = <0.001

cohort group differences: p = <0.001

Table 1.9B. Proportion socially isolated by age and cohort - HRS, Waves 1-3 (2006-2016): Women

	Cohort				
Age Interval	1915-1924	1925-1934	1935-1944	1945-1954	1955-1964
50-59				0.13	0.14
60-69			0.15	0.16	0.15
70-79		0.19	0.18	0.13	
80-89	0.30	0.27	0.20		

age group differences: p = <0.001

cohort group differences: p = <0.001

Table 1.10A. Cross-sectional means of the social isolation index by inclusion of relationship status and gender among U.S. adults - MIDUS

	Wave 1 (1995-96)		Wave 2 (2004-06)		Wave 3 (2013-14)	
Prevalence, mean (SD)	Men	Women	Men	Women	Men	Women
Including relationship	1.29	1.21	1.25	1.24	1.35	1.31
status (0-4)	(0.97)	(0.94)[d]	(0.96)	(0.98)	(0.99)	(0.99)
Excluding relationship	1.14	1.06	1.12	0.99	1.20	1.03
status (0-3)	(0.83)	(0.77)[d]	(0.83)	(0.84)[d]	(0.83)	(0.85)[d]

Notes: a = <0.05 difference between Waves 1 and 2; b = <0.05 difference between Waves 1 and 3

c = <0.05 difference between Wave 2 and 3; d = <0.05 difference between men and women

Age range for Wave 1 is 25-75; Wave 2: 35-86; Wave 3: 44-93

Table 1.10B. Cross-sectional means of the social isolation index by inclusion of relationship status and gender among U.S. adults – HRS

	Wave 1 (2006/08)		Wave 2 (2010/12)		Wave 3 (2014/16)	
Prevalence, mean (SD)	Men	Women	Men	Women	Men	Women
Including relationship	1.41	1.42	1.50	1.49	1.45	1.50
status (0-4)	(1.06)	(1.10)	(1.06)[a]	(1.10)[a]	(0.95)[c]	(1.03)[bd]
Excluding relationship	1.23	1.02	1.25	1.10	1.20	1.12
status (0-3)	(0.85)	(0.85)[d]	(0.81)	(0.80)[ad]	(0.74)[c]	(0.77)[bd]

Notes: a = <0.05 difference between Waves 1 and 2; b = <0.05 difference between Waves 1 and 3

c = <0.05 difference between Wave 2 and 3; d = <0.05 difference between men and women

Age range for all waves is 50 and older

Table 1.11A. Cross-sectional means of the social isolation index by inclusion of relationship status, age, and gender among U.S. adults - MIDUS

	Wave 1 (1995-96)		Wave 2 (2004-06)		Wave 3 (2013-14)	
Prevalence, mean(SD)	Men	Women	Men	Women	Men	Women
Including relationship status (0-4)						
25-39 (Young Adulthood)	1.40 (0.95)	1.20 (0.93)[j]	1.28 (0.82)	1.04 (0.96)	-	-
40-64 (Midlife)	1.26 (1.05)[d]	1.20 (1.01)	1.27 (0.95)	1.24 (0.93)	1.37 (0.86)	1.28 (0.92)
65-79 (Older Adulthood)	1.08 (0.83)[eg]	1.29 (0.83)	1.17 (0.98)	1.31 (1.00)[e]	1.30 (1.07)[b]	1.30 (1.04)
80+ (Late Life)	-	-	1.17 (0.82)	1.50 (1.24)	1.38 (1.12)	1.54 (0.85)
Excluding relationship status (0-3)						
25-39 (Young Adulthood)	1.18 (0.80)	1.08 (0.78)	1.19 (0.70)	0.92 (0.78)[j]	-	-
40-64 (Midlife)	1.15 (0.93)	1.06 (0.82)[j]	1.13 (0.83)	1.03 (0.82)	1.21 (0.72)	1.08 (0.79)
65-79 (Older Adulthood)	0.97 (0.70)[eg]	0.99 (0.63)	1.04 (0.85)	0.91 (0.85)	1.17 (0.91)[b]	0.95 (0.84)[j]
80+ (Late Life)	-	-	0.95 (0.69)	1.02 (0.91)	1.17 (0.96)	0.94 (0.90)

Notes: a = <0.05 difference between Waves 1 and 2; b = <0.05 difference between Waves 1 and 3; c = <0.05 difference between Wave 2 and 3; d = <0.05 difference between young adulthood and midlife; e = <0.05 difference between young adulthood and older adulthood; f = <0.05 difference between young adulthood and late life; g = <0.05 difference between midlife and older adulthood; h = <0.05 difference between midlife and late life; i = <0.05 difference between older adulthood and late life; j = <0.05 difference between men and women

Age range for Wave 1 is 25-75; Wave 2: 35-86; Wave 3: 44-93

Table 1.11B. Cross-sectional means of the social isolation index by inclusion of relationship status, age, and gender among U.S. adults - HRS

	Wave 1 (2006/08)		Wave 2 (2010/12)		Wave 3 (2014/16)	
Prevalence, mean(SD)	Men	Women	Men	Women	Men	Women
Including relationship status (0-4)						
50-64 (Midlife)	1.40 (0.81)	1.33 (0.89)[j]	1.49 (0.95)[a]	1.38 (0.97)[aj]	1.48 (0.89)[b]	1.43 (0.96)[bc]
65-79 (Older Adulthood)	1.36 (1.29)	1.36 (1.27)	1.47 (1.17)[a]	1.48 (1.22)[ag]	1.37 (0.97)[cg]	1.44 (1.04)[bj]
80+ (Late Life)	1.62 (1.36)[hi]	1.84 (1.18)[hij]	1.65 (1.31)[hi]	1.96 (1.18)[ahij]	1.55 (1.18)[ci]	1.90 (1.12)[hij]
Excluding relationship status (0-3)						
50-64 (Midlife)	1.28 (0.63)	1.10 (0.70)[j]	1.25 (0.70)	1.15 (0.71)[aj]	1.22 (0.67)	1.19 (0.72)[bc]
65-79 (Older Adulthood)	1.18 (1.04)[g]	0.94 (0.99)[gj]	1.25 (0.90)[a]	1.05 (0.89)[agj]	1.19 (0.77)[c]	1.06 (0.79)[bgj]
80+ (Late Life)	1.17 (1.10)[h]	0.97 (0.95)[hj]	1.25 (1.02)	1.07 (0.88)[ahj]	1.16 (0.92)	1.07 (0.86)[bhj]

Notes: a = <0.05 difference between Waves 1 and 2; b = <0.05 difference between Waves 1 and 3; c = <0.05 difference between Wave 2 and 3; d = <0.05 difference between young adulthood and midlife; e = <0.05 difference between young adulthood and older adulthood; f = <0.05 difference between young adulthood and late life; g = <0.05 difference between midlife and older adulthood; h = <0.05 difference between midlife and late life; i = <0.05 difference between older adulthood and late life; j = <0.05 difference between men and women

Age range for all waves is 50 and older

CHAPTER TWO. TRAJECTORIES OF SOCIAL ISOLATION ACROSS ADULTHOOD

Social isolation has been linked to a multitude of adverse outcomes across the life course, including poor health, high healthcare spending, and a lack of informational, emotional, and instrumental resources (Cantarero-Prieto et al. 2018; Flowers et al. 2017; Holt-Lunstad et al. 2010; House et al. 1988; Umberson et al. 2010). Given the key role social isolation plays in health and well-being, it is essential that research better understands how social isolation operates across adulthood. The increasing availability of U.S. longitudinal datasets has led researchers to begin investigating trajectories of social isolation within individuals as they age (Caspi et al. 2006; Petersen et al. 2016; Umberson et al. 2022; Yang, Li, and Ji 2013). Research on social isolation has used a variety of longitudinal model specifications, such as growth curve and autoregressive models, without explicitly comparing fit across these models. In addition, although previous research has documented cohort and gender differences in social isolation, few studies have examined whether these factors are associated with trajectories of social isolation (Cudjoe et al. 2020; Fischer 2011; Naito et al. 2021; Putnam 2000).

Determining the best fitting longitudinal model of social isolation can help provide important information on how social isolation is changing within individuals as they age. For example, is the trajectory of social isolation primarily a function of isolation at a younger age? Does social isolation exhibit a linear increase with age? Is it a combination of these patterns? Or does it follow some other pattern? The lack of data on which longitudinal model specification best fit the trajectory of social isolation has led researchers to make ad hoc decisions on which model specifications to use in their research. However, using incorrect model specifications can lead to inaccurate and biased findings.

In addition to determining the best fitting trajectory of social isolation, it is also important to examine factors associated with trajectories of social isolation. In particular, assessing whether factors predict the mean levels or patterns of change of social isolation as well as whether the effect of these factors differ by age can provide key insights into group differences in social isolation. Birth cohorts are a particularly important factor to examine as they may provide insight into future trends of social isolation. Research on cohort differences in social isolation has produced opposing findings. Some literature claims that social isolation has been increasing among recent U.S. birth cohorts, while others suggesting that levels of isolation have remained stable (Ang 2019; Fischer 2011; Marsden and Srivastava 2012; Putnam 2000; Wang and Wellman 2010). Despite the numerous studies on social isolation by cohort, these studies primarily use repeated cross-sectional data or do not test multiple model specifications. Examining trajectories of social isolation with the best fitting empirical model could provide better estimates into the role cohorts play in the trajectory of social isolation.

Gender is also a key factor to investigate when examining trajectories of social isolation. Disparities in social isolation can cause differential access to informational, emotional, and instrumental resources, which can further exacerbate disparities in health, job opportunities, and social support (Cudjoe et al. 2020; Gottlieb and Bergen 2010; National Academies of Sciences, Engineering, and Medicine 2020). Thus, better understanding disparities in social isolation may help in understanding mechanisms contributing to gender disparities in these other key domains of interest. As with literature on cohort differences, gender differences in social isolation have also been contested, with research mostly using cross-sectional data or only examining one model specification (Cornwell et al. 2008; Cudjoe et al. 2020; McPherson et al. 2006; Röhr et al. 2021; Vandervoort 2000).

This chapter investigates the trajectory of social isolation across the adult life course in the United States and examines how social isolation varies by cohort and gender. Specifically, I address three research questions. First, what is the best fitting longitudinal model of social isolation? Second, are there cohort or gender differences in mean levels or patterns of change of social isolation? Third, do cohort and gender differences in social isolation vary by age?

BACKGROUND

Social Isolation Across the Adult Life Span

Research on social isolation has primarily focused on older populations because older adults are more likely to live alone, experience the loss of family and friends, and have physical and cognitive limitations (Cornwell and Waite 2009b; Holt-Lunstad et al. 2010; National Academies of Sciences, Engineering, and Medicine 2020). While older adults are at an increased risk of social isolation, isolation can occur earlier in adulthood as well (Hämmig 2019). Being socially isolated earlier in adulthood may lead to higher rates of isolation later in life. Additionally, being socially isolated earlier in life may compound the negative effects of social isolation, such as poor health and low resources, across multiple life stages. Therefore, research should shift to studying social isolation from a life course perspective to better understand how social isolation operates as individuals age.

The life course perspective is a theoretical orientation which views the life span as age-graded patterns that are embedded in social and historical context (Elder et al. 2003). A key component of this perspective is the principle of life span development, which posits that human development and aging are life-long processes (Elder 1998; Elder and Giele 2009; Elder et al.

2003). This principle suggests that isolation is dynamic, evolving over the life span. Thus, examining social isolation at one point in time is not sufficient to capture changes in isolation (Teas et al. 2023). A more comprehensive understanding of social isolation would provide key insights into whether social isolation increases, decreases, or remains the same as individuals age. This could provide information on which life stages to focus interventions as well as help researchers better understand the stickiness or malleability of social isolation.

Longitudinal Models of Social Isolation

While previous research has called for longitudinal data to better assess the relationship between social isolation and health (Cornwell and Waite 2009b; Umberson et al. 2010), most of this research has used cross-sectional data (Coyle and Dugan 2012; Cudjoe et al. 2020) or longitudinal data on just the health outcome variable (Brummett et al. 2001; Kobayashi and Steptoe 2018; Seeman et al. 2001; Shankar et al. 2013; Steptoe et al. 2013). Those that have assessed social isolation longitudinally have tended to use transition probability analysis, growth curve models, or latent class growth models (Luo and Li 2022; Petersen et al. 2016; Umberson et al. 2022; Yang et al. 2013). Yet, no research has comprehensively examined the trajectory of social isolation across multiple model specifications. Since there is no one theory that best captures the trajectory of social isolation, in this chapter I use previous longitudinal analyses of social isolation as well as theories of the longitudinal structure of other social and health outcomes to guide this analysis. I base my longitudinal models on research by Bollen and Gutin (2021), who tested the longitudinal structure of self-rated health in young adults. This leads me to five potential longitudinal models of social isolation: enduring, spontaneous, lagged effects, life course, and hybrid (Bollen and Gutin 2021). Identifying the correct longitudinal model is important for producing an accurate and unbiased understanding of social isolation.

The enduring perspective suggests that social isolation is stable across the life span. The reason for this stability can be due to multiple factors. First, isolation may partially be due to biological factors. Research has found that brain structure is associated with functioning in affective and social domains, which may affect social connections with others (Holmes et al. 2012; Kagan and Snidman 2004). Second, personality may play a role in social isolation. Introverts may be less likely to have large social networks and participate in group activities than extroverts. Third, stable self-perceptions, for example thoughts of being a loner, may impede some individuals from engaging in social interactions, thus fulfilling their self-perceptions. These and other time-invariant variables may contribute to an enduring level of social isolation across the life span. This theory is supported by Cornwell and colleagues (2021) and Ertel et al. (2009), who find that while connections change as individuals age, these losses and additions offset each other, leading to relative stability in social network ties across the life span.

On the other hand, the spontaneous view posits that social isolation has no specific longitudinal structure. Rather, social isolation is largely dependent on factors occurring around the time of the survey assessment. Most social isolation measures ask individuals to report on activities which have occurred over the past month or year. These types of measures are sensitive to recent events (Brissette, Cohen, and Seeman 2000). For example, an individual may experience an injury, such as a broken foot, which may affect their level of social isolation at one point in time but not the next. This view suggests that social isolation does not change consistently because people's contexts are always changing, and those current contexts affect social isolation.

The lagged effects perspective suggests that current social isolation is largely dependent on previous levels of social isolation. While social isolation reflects stability in both the lagged effects and enduring perspectives, the lagged effects perspective represents stability over a shorter period than the enduring perspective. The lagged effects perspective emphasizes the importance of recent history as the predominant factor influencing social isolation from one time to the next. Longitudinal research on loneliness has supported the lagged effects hypothesis (Griffin et al. 2022). In particular, Petersen and colleagues (2016) found that 60 percent of respondents who reported loneliness in one year reported it in the next year. Similarly, 87 percent of those who reported not feeling lonely continued to report no loneliness a year later. Additional research has found that those who reported loneliness in older adulthood were more likely to have experienced loneliness at a previous life stage than their non-lonely counterparts (Victor et al. 2022). However, research on the stability of social isolation has been mixed. Some research has found stability in patterns of social isolation in mid- and late-life, while others have found little stability from childhood to adulthood (Lay-Yee et al. 2021; Luo and Li 2022).

The life course perspective suggests that throughout the life span, individuals experience critical transitions such as leaving home, attending college, entering full time employment, getting married, and becoming a parent (Elder and Shanahan 2006; George 1993; Shanahan 2000). These transitions may shape trajectories of social isolation. For example, those who are more educated are less likely to be socially isolated compared to those who are less educated (McPherson et al. 2006). Therefore, attending college can potentially impact trajectories of social isolation. The life course perspective suggests that these transitions, as well as their timing, vary from person to person (Elder et al. 2003; Shanahan 2000).

Last is the hybrid model, which posits that the enduring, spontaneous, lagged effect, and life course perspectives are not mutually exclusive. For example, social isolation may be informed by both lagged effects and a life course perspective, whereby social isolation is impacted by both previous waves of social isolation as well as a growth process. Furthermore, the enduring and lagged effects hypotheses could be operating simultaneously as social isolation is impacted by both time-invariant factors and the past.

Overall, then, I postulate that a hybrid model will best capture the complexity of the longitudinal character of this measure.

> *Hypothesis 1:* A hybrid model will best fit the longitudinal structure of social isolation compared to the enduring, spontaneous, lagged effects, and life course perspective models alone.

Cohort Differences in Trajectories of Social Isolation

The life course perspective suggests that individuals are shaped by the historical times and places they experience over their lifetime, thus highlighting the importance of birth cohorts (Elder 1998; Elder and Giele 2009; Elder et al. 2003). Changes in social and historical circumstances could lead to divergent trends in social isolation across cohorts. Previous research has posited that social isolation has increased due to the large amount of societal change that has occurred in the past half century (Parigi and Henson 2014; Putnam 2000). Meanwhile, research by Fischer (2009, 2011) and others find that levels of isolation have remained stable across birth cohorts (Ang 2019; Antonucci et al. 2019; Marsden and Srivastava 2012; Wang and Wellman 2010). In the previous chapter, I find that more recent cohorts are more isolated than earlier born cohorts in MIDUS. While findings indicate that levels of isolation differ by birth cohort in HRS, the direction of these findings is mixed. More research is needed to determine whether there are cohort differences in social isolation. In particular, examining cohort differences in trajectories of social isolation will help determine whether divergent trends in social isolation exist. This could help provide insight into future trends of social isolation.

Although numerous studies have examined social isolation over time, most literature has used repeated cross-sectional data which examines synthetic cohorts, or individuals from different cohorts at different points in time (Marsden and Srivastava 2012; McPherson et al. 2006). Analysis using synthetic cohorts assumes that the repeat cross-sections represent true cohorts, which may not be the case as the composition of cohorts change over time (Yang and Land 2013). For example, research by McPherson et al. (2006) found that from the mid-1980s to mid-2000s network size shrunk by a third. However, this study did not take into account the cohort composition of the populations analyzed, thus conflating period and cohort effects. Accelerated longitudinal panel data can provide a more representative picture of cohorts because this data follows the same individuals over time and is comprised of multiple cohorts.

Modeling strategies that do not properly fit the trajectory of social isolation can also provide inaccurate estimates of cohort differences in social isolation. Some models, such as conventional linear regression models, can cause specification errors or an identification problem which make it impossible to separate age and cohort effects (Yang and Land 2013). The limited research that has used proper study designs and analyses have examined dimensions of social isolation separately (Ang 2019). Yet, previous literature has found that the absence of multiple social ties is what confers the greatest risk for health (Berkman and Breslow 1983). This suggests further research is needed to examine broader trends in social isolation using the best fitting longitudinal model of social isolation.

Although large societal changes have occurred in recent decades which may suggest that isolation has increased in more recent cohorts, other advances, such as in communication technologies, have supplemented social connections (Fischer 2011; Vogels 2019; Wang and Wellman 2010). Additionally, literature which had found large increases in social isolation by birth cohort has been challenged (Fischer 2009; Lemann 2015; Paik and Sanchagrin 2013; Paxton 1999). In accordance with findings from my previous empirical chapter and previous literature which has found adaptability in social connectedness, I hypothesize that:

> *Hypothesis 2:* There are no cohort differences in mean levels of isolation or rates of change of social isolation across adulthood.
>
> *Hypothesis 3:* The relationship between social isolation and cohort does not differ by age.

Gender Differences in Trajectories of Social Isolation

Previous research has observed inconsistent evidence of gender disparities in social isolation. While some research has found that women are more isolated than men, others have found the opposite, or have found no significant gender differences in social isolation (Cornwell et al. 2008; Cudjoe et al. 2020; Naito et al. 2021; Röhr et al. 2021; Steptoe et al. 2013; Vandervoort 2000). In the previous chapter, descriptive results by age suggested that men are more isolated than women in midlife. However, this gap narrows in older adulthood and reverses in late life, with women becoming more isolated than men. Although gender disparities in mean levels of social isolation have been documented, evidence regarding whether these disparities change within individuals as they age has been limited. Determining whether men or women have different trajectories of social isolation can provide insights into at-risk groups (Read, Comas-Herrera, and Grundy 2020). Since being socially isolated is linked to lower access to resources, worse health, less job opportunities, and other adverse outcomes, social isolation may be a mechanism contributing to disparities in many domains of life (Cudjoe et al. 2020; Gottlieb and Bergen 2010; National Academies of Sciences, Engineering, and Medicine 2020).

The limited literature on gender differences in trajectories of social isolation suggests that men and women have divergent trajectories. For instance, Fischer and Beresford (2015) found that as men and women age from their 50s to 60s, men exhibit steeper upward trajectories of social isolation relative to women. Meanwhile, research by Umberson and colleagues (2022) found that age trajectories of social isolation are steeper in women than men. While these studies provide key insights, they use different modeling specifications: lagged dependent variable models (Fischer and Beresford 2015) and multilevel growth curve models (Umberson et al. 2022). These different model specifications may have led to conflicting estimates of gender disparities. It is important to first identify the longitudinal model that best fits the data before estimating gender differences.

Although no research has determined the best fitting longitudinal model of social isolation, the findings from Umberson and colleagues (2022) and my previous empirical chapter suggest that while men are more isolated in young adulthood and midlife, women become more isolated than men with advancing age. Men may be more isolated in young adulthood due to gendered systems in the United States which promote self-sufficiency, independence, and controlled emotion among men and interpersonal relationships and intimacy among women (Courtenay 2000; Erickson 2005; Umberson et al. 1996, 2014; Williams 2008). Meanwhile, increases in social isolation among women is primarily due to their steeper increases in widowhood, particularly beginning in older adulthood. Overall, I expect to find similar results in this analysis, leading me to hypothesize:

> *Hypothesis 4:* Men will have higher mean levels of isolation than women, but women will have steeper increases in social isolation by age than men.

Hypothesis 5: The relationship between social isolation and gender will differ by age, with men being more isolated than women in young adulthood before disparities converge in midlife and reverse in late life, with women becoming more isolated than men.

HYPOTHESIZED LONGITUDINAL MODELS

Figures 2.1A through 2.1E display proposed longitudinal models of social isolation (see Bollen and Gutin 2021). The spontaneity hypothesis is not depicted because this perspective hypothesizes that social isolation is unpredictable. Therefore, in this model there is no systematic longitudinal pattern of social isolation. Figure 2.1A displays the enduring hypothesis, which suggests that social isolation is stable across the life span. This model is represented by a latent time-invariant intercept that determines social isolation at each age. Variability in social isolation in the enduring model arises due to changes in the intercept at each age and in the error term for social isolation. Figure 2.1B illustrates the lagged effects hypothesis, where social isolation is a function of previous social isolation. In the lagged effects hypothesis, social isolation reflects stability, but not for as long of a period as the enduring hypothesis. Figure 2.1C shows the life course perspective, which suggests that social isolation follows a trajectory that is determined by life experiences and contexts. This perspective is best represented by a latent growth curve model that allows individuals to have different intercepts and slopes. Lastly, Figures 2.1D and 2.1E display examples of hybrid models using autoregressive latent trajectory (ALT) models (Bollen and Curran 2004; Bollen and Zimmer 2010). The ALT model is a general longitudinal model that includes aspects of other longitudinal models. Specifically, Figure 2.1D adds lagged effects to a growth curve model and Figure 2.1E combines lagged effect and time-invariant components (Bollen and Curran 2004). All figures include controls for race/ethnicity and educational attainment.

DATA AND METHODS

Study Samples

I use data from the National Survey of Midlife Development in the United States (MIDUS) and the Health and Retirement Study (HRS) to determine the best fitting trajectory of social isolation across the adult life course and examine how the trajectory of social isolation varies by birth cohort and gender (see the Data Section from Chapter One for more detail on these datasets). Both datasets use an accelerated longitudinal design which follows individuals from multiple birth cohorts as they age. Data from MIDUS comes from three waves, collected in 1995-96, 2004-06, and 2013-14. In this chapter, I restrict the MIDUS analysis to respondents from the national random digit dial sample because it has valid sampling weights. For the HRS sample, I pool data from 2006 and 2008, 2010 and 2012, and 2014 and 2016 to create full samples of HRS participants from the Leave-Behind Questionnaires.

My analytic samples include respondents with valid control measures (race/ethnicity and educational attainment). Respondents born before 1915 (Young Progressives) were excluded because of their small sample size. Additionally, respondents in HRS born after 1954 (Late Baby Boomers) were excluded because they did not enter the survey until 2016. Missing data is addressed through full information maximum likelihood (Arbuckle 1996). This method uses available data from each respondent and assumes Missing at Random (MAR) to compute maximum likelihood estimates that provides parameter estimates without imputing any data. This leads me to an analytic sample of 3,052 for MIDUS and 24,501 for HRS.

Measures

Social isolation is measured the same way as in the previous empirical chapter; it is a sum of four types of social relationships: relationship status, frequency of contact with friends and family, religious group attendance, and community involvement. This results in an index ranging from zero to four, with a higher score indicating more isolation (see the Measures Section from Chapter One for more detail). I structured the data with age as the metric of time, to better understand changes in social isolation within people as they age, which has more substantive relevance than changes across survey years. Age was grouped into 5-year age ranges in MIDUS and 3-year age ranges in HRS to help limit the amount of missing data caused by structuring the data by age (an example of this data structure is shown in Table 2.1). These ranges were selected to display meaningful changes in social isolation by age while also minimizing repeat measures of social isolation within-person for each age group. For example, the Leave Behind questionnaire in HRS was collected every four years, which means that people were 3 to 5 years older between waves depending on the month respondents participated in the survey. Therefore, I chose 3-year age ranges in HRS to minimize repeat measures of social isolation within-person for each age group while also making the categories large enough to show potential change in social isolation. Age groups in MIDUS ranged from 25-29 to 80 and older and in HRS from 50-52 to 89 and older. Age groups were top coded to address sparse data at older ages. For respondents with two values of social isolation within an age range, particularly for the top coded categories, the average value of social isolation was taken. Structuring the data by age group created more than five assessment periods, which allowed me to relax some model assumptions I would have had to make with the original three waves of data.

Other variables of interest include cohort, gender, race/ethnicity, and educational attainment. Using birth years, I grouped respondents into six 10-year birth cohorts: 1915-24

(Jazz Age Babies), 1925-34 (Depression Kids), 1935-44 (War Babies), 1945-54 (Early Baby Boomers), 1955-1964 (Late Baby Boomers), and 1965-1974 (Generation X; Hughes et al. 2005; Yang and Lee 2009). HRS spans from Jazz Age Babies to the Late Baby Boomers, while MIDUS ranges from Jazz Age Babies to Generation X. Gender was assessed with a dummy variable (0 = men, 1 = women). Models also account for race/ethnicity (non-Hispanic White [reference], non-Hispanic Black, Hispanic, and non-Hispanic Other Races) and educational attainment (less than high school, high school degree [reference], some college, college degree or higher).

Analytic Approach

I tested various longitudinal models of social isolation to determine which is most consistent with the empirical data. I first conducted these tests using MIDUS, then replicated them using HRS. In order to measure the cumulative effects of the four social relationship types, as well as for parsimony, I make the assumption that there are no distinct effects or trajectories by social relationship type. To test the enduring hypothesis, I use a time-invariant variable model corresponding to Figure 2.1A,

$$Y_{it} = \alpha_t + \eta_i + \varepsilon_{it} \tag{2.1}$$

where Y_{it} is the social isolation index for individual i at age group t, α_t is the intercept at age group t, η_i is the time-invariant variable, and ε_{it} is the random error that varies across person and age with a mean of zero and is uncorrelated with η_i.

The lagged effects hypothesis is captured by,

$$Y_{it} = \alpha_t + \rho_{t,t-1} Y_{i,t-1} + \varepsilon_{it} \tag{2.2}$$

where $Y_{i,t-1}$ is the lagged value of social isolation and $\rho_{t,t-1}$ is the autoregressive regression coefficient of the magnitude of the lagged effects. This equation is modeled in Figure 2.1B. I additionally tested whether autoregressive coefficients are equal across age groups.

Next, the life course perspective is represented by a latent growth curve model (Figure 2.1C), which suggests that social isolation follows a trajectory by age[2]. The model is specified as such,

$$Y_{it} = \alpha_i + \lambda_t \beta_i + \varepsilon_{it} \tag{2.3}$$

where α_i is the random intercept, β_i is the random slope, λ_t is the age trend variable, and ε_{it} is the random error with a mean of zero and is uncorrelated with α_i and β_i. Including random intercepts and slopes allows every individual to have their own starting point and rates of change.

As stated above, there is no systematic longitudinal influence on social isolation in the spontaneous hypothesis. Therefore, the spontaneous hypothesis is tested by examining the R-squared values of the previous models. Very low R-squared values would lend support to the spontaneous hypothesis.

Lastly, these models are not mutually exclusive and can be similarly operating in a hybrid model. One hybrid model is the autoregressive latent trajectory (ALT) growth model (Bollen and Curran 2004; Bollen and Zimmer 2010), where both the life course and lagged effects perspectives are represented.

$$Y_{it} = \alpha_i + \lambda_t \beta_i + \rho_{t,t-1} Y_{i,t-1} + \varepsilon_{it} \tag{2.4}$$

[2] Quadradic growth curve models did not converge.

In this equation, the life course perspective is signified by the latent intercept and slope and the lagged effects hypothesis is signified by the autoregressive terms. This model is represented in Figure 2.1D. Likewise, the enduring and lagged effects hypotheses can be combined to create an intercept only ALT model (Figure 2.1E).

$$Y_{it} = \alpha_t + \rho_{t,t-1} Y_{i,t-1} + \eta_i + \varepsilon_{it} \tag{2.5}$$

This model includes both autoregressive terms and a time-invariant variable. In these two ALT models, Y_{it} is treated as predetermined, with a mean and person-specific deviation, because lagged values are not estimated for the first time period since there are no previous time periods to predict this value. These longitudinal models provide multiple plausible hypotheses regarding the trajectory of social isolation.

To examine cohort and gender differences in the trajectory of social isolation I incorporate these variables in two ways. First, I add cohort and gender as predictors of the latent growth parameters (e.g., intercept and slope) to determine whether these variables are related to mean levels of isolation or rates of change of social isolation. Second, I add cohort and gender as covariates on measures of social isolation (similar to race/ethnicity and education) to examine whether cohort and gender differences in social isolation vary by age.

Successive models adding equality constraints were fit to examine whether cohort and gender have similar associations with social isolation by age. These two modeling strategies are run separately as the latter specification controls out the effects of cohort and gender. The 10-year birth cohorts were treated as continuous as done in previous literature (Yang et al. 2021; Yang and Lee 2009). Sensitivity analyses were run including birth cohorts as dummy variables which resulted in similar findings.

Analyses were conducted using the lavaan package in R (Rosseel 2012). I used robust maximum likelihood to more accurately estimate standard errors and to allow for possible nonnormality of the error variables. Sensitivity analyses suggested that variances of social isolation were similar across age groups. Thus, variances of social isolation were constrained to be equal across age groups to aid in convergence of the models. Measures of social isolation at each age group include controls for race/ethnicity and educational attainment, as shown in Figure 1, to correct for the influence of these covariates in model estimates (Stoel, van den Wittenboer, and Hox 2004). With the addition of these controls, variables that were used to calculate the person-specific weights in MIDUS and HRS -- age, birth cohort, gender, race/ethnicity, educational attainment, and marital status -- are accounted for in the models (Brim et al. 2018; Ofstedal et al. 2011). Using variables involved in the computation of the weights in the analysis allows me to account for selection bias in sampling and approximate unbiased and consistent estimates without weighting the data (Asparouhov 2005; Solon, Haider, and Wooldridge 2015). Sensitivity analyses were conducted both removing and adding covariates on social isolation. Not weighting the data allows me to use full information maximum likelihood (FIML) to address the large amount of missing data due to attrition and data structure (see Table 2.1 for an example). FIML (or Casewise Maximum Likelihood), like multiple imputation, only assumes Missing at Random (MAR) rather than Missing Completely at Random (MCAR). In addition, unlike multiple imputation I do not need to impute any data and estimate the model only on the original data. Additionally, in well-specified models, unweighted models provide better estimation efficiency than weighted models (Asparouhov 2005; Muthén and Satorra 1995).

Model fit statistics were used to determine the best fitting longitudinal model. Model fits were assessed using multiple fit statistics, as suggested by previous literature (Bollen 1989). In particular, I assessed the chi-squared test statistic, Comparative Fit Index (CFI), Tucker Lewis Index (TLI), Root Mean Square Error of Approximation (RMSEA), and the Bayesian Information Criterion (BIC). While there has been some controversy regarding cutoff values, small and non-significant chi-squared test statistics, CFI and TLI values greater than 0.95, RMSEA values less than 0.06, and BIC values less than zero are the most common thresholds for good model fit (Bentler 1990; Bollen 1989; Hu and Bentler 1999; Raftery 1995; Tucker and Lewis 1973).

RESULTS

Descriptive Results

The descriptive statistics in Tables 2.2A and 2.2B report the weighted variables for the analytic samples in MIDUS and HRS, respectively. Social isolation ranges from 0 to 4, with mean values varying by age. In MIDUS, the average social isolation score is 1.42 (SD=0.90) at ages 25-29 and 1.40 (SD=1.02) at ages 80 and older. Similarly, in HRS, the average isolation score is 1.39 (SD=0.98) at ages 50-52, but is 2.13 (SD=1.00) at ages 89 and older. Overall, the samples are mostly white (81 percent in MIDUS and 75 percent in HRS), have slightly more women (53 percent) than men, and have majorities with at least some college education (56 percent in MIDUS and 53 percent in HRS). Birth cohorts ranged from 1915 to 1974, with the largest proportion of respondents in the 1945-1954 and 1955-1964 cohorts.

Longitudinal Models of Social Isolation

Tables 2.3A and 2.3B present fit statistics for six longitudinal models: the Latent Time Invariant Model, Autoregressive Model (with and without autoregressive coefficients constrained to be equal across age groups), Linear Growth Curve Model, and the Autoregressive Latent Trajectory (ALT) Intercept Only Model (with and without the autoregressive coefficients constrained to be equal across age groups). The Spontaneous Model is not included because this model suggests that there is no systematic longitudinal pattern of social isolation and is assessed by examining R-squared values. Additionally, the ALT Growth Model did not converge in either dataset.

All six longitudinal models in MIDUS have good model fit statistics, with the ALT Intercept Only Model with autoregressive coefficients constrained to be equal across age groups (ARs Constrained) having the best model fit. The ALT models have the lowest chi-squared test statistic of any of the tested models. The statistical power to detect even minor errors in the model goes up when the sample size is large as is the case for these models. This helps to explain the statistically significant chi-squared statistics (Bollen 1989). The magnitude of the fit statistics are less influenced by sample size and provide additional perspectives on model fit. The CFI and TLI of the ALT Intercept Only Model are close to 1, 0.987 and 0.980 respectively, which is the highest of all the models. The RMSEA is the lowest of all the models at 0.008 and the BIC is negative and the highest of all the models in absolute magnitude at -631, which suggests superior fit compared to the saturated model (Raftery 1995). The ALT Intercept Only Model with ARs Constrained was still the best fitting model across all fit statistics when excluding all covariates as well as when adding gender and cohort as direct effects on social isolation (Appendix Table 2.1A. and Table 2.2A).

In addition to having the best model fit across all assessed criteria, the ALT Intercept Only Model with ARs Constrained is considered the best fitting model for several other reasons. First, the slope of social isolation in the Linear Growth Curve Model is not significant (Appendix Table 2.3A). Even though the ALT Growth Model did not converge, a nonsignificant slope in the Linear Growth Curve Model suggests that neither model fits the data the best. Second, results from all models with autoregressive equations demonstrate a significant and positive effect of social isolation at previous ages, supporting the inclusion of lagged effects in the models. Third, in addition to the better model fit when constraining the autoregressive coefficients to be equal, the autoregressive coefficients are similar across age groups when not imposing this constraint. Last, a model which includes both enduring and lagged effects fits better than each model alone, which suggests the advantage of a hybrid model. Given the complexity of social isolation, it makes theoretical sense that a hybrid model would fit the data the best. This supports my first hypothesis that a hybrid model will best fit the longitudinal structure of social isolation compared to the enduring, spontaneous, lagged effects, and life course perspective models alone.

Similarly, in HRS (Table 2.2B), the ALT Intercept Only Model is the best fitting longitudinal model. Compared to MIDUS, the HRS ALT Intercept Only Model fits best when the autoregressive coefficients are not constrained to be equal. This model has a CFI of 0.975 and TFI of 0.959, which are the highest and second highest values, respectively, compared to the other five models. This model also has a RMSEA of 0.013 and chi-squared value of 829, which are the lowest compared to the other five models. It also has the most negative BIC, -560. It is important to note that the Linear Growth Curve Model would not converge in HRS with covariates for race/ethnicity. Therefore, the fit reported is the model fit controlling only for educational attainment. However, results from the Linear Growth Curve Model show a small (0.003) mean slope that does not have a significant variance (Appendix Table 2.3B). These results suggest that including a slope factor may not substantively improve the understanding of trajectories of social isolation. Sensitivity analyses which do not include controls for educational attainment and race/ethnicity or that adds gender and cohort as direct effects on social isolation (Appendix Table 2.1B and Appendix Table 2.2B) suggest that while including controls leads to better fit statistics for all six models, the ALT Intercept Only Model still has the best model fit overall.

Tables 2.4A and 2.4B show parameter estimates for the best fitting model in MIDUS and HRS, both of which were the ALT Intercept Only Model. Results from MIDUS suggest that levels of social isolation vary significantly across individuals ($p = <0.001$). Of particular interest are the autoregressive parameters, which indicate how much social isolation at one age predicts social isolation at the next age. Given that the model with autoregressive coefficients constrained to be equal across age groups has the best model fit, this suggests that the path dependence of social isolation is similar across adulthood. The autoregressive coefficients are highly significant ($p = <0.001$), which suggests there is some stability in social isolation as individuals age. The coefficient is relatively small (0.31). However, it is important to note that this estimate is the lagged effect after accounting for the latent intercept, which captures unobserved heterogeneity.

Next, the R-squared values specify how much of the variation in social isolation is explained by each model. In MIDUS, R-squared values range from 0.55 at ages 30-34 to 0.62 at ages 80 and older. This indicates that around 60 percent of the variance in social isolation is explained by time-invariant factors, lagged values, controls for race/ethnicity and educational attainment, and other elements of the model. The relatively high R-squared values indicate that the spontaneous hypothesis is not the best fitting longitudinal model.

Results from the ALT Intercept Only Model in HRS (Table 2.4B) exhibit similar findings as the MIDUS results, with a few differences. First, while social isolation also varies significantly across individuals ($p = <0.001$) in HRS, the mean of social isolation is higher (1.39) than in MIDUS (0.92). Since the ALT model fits better without equality constraints this suggests that the stability of social isolation changes across adulthood. The autoregressive parameters in

HRS are highly significant ($p = <0.001$) and increase, from 0.12 to 0.31, as individuals age, indicating a slight increase in the stability of social isolation from mid- to late-life. Most of the autoregressive parameters are larger in MIDUS (0.31) than HRS. However, the R-squared values are larger in HRS than MIDUS, ranging from 0.62 to 0.72 at ages 50 and older in HRS, compared to R-squared values in MIDUS which range from 0.55 to 0.62. This suggests that the latent intercept and covariates (race/ethnicity and educational attainment) are more predictive of variability in social isolation in HRS than in MIDUS. When running sensitivity analyses excluding controls for race/ethnicity and educational attainment, the R-squared values drop minimally, suggesting that differences at the latent intercept are explaining a large part of the variance in social isolation (Appendix Table 2.4B). Lastly, models indicate that Blacks and Hispanics are more isolated than Whites and higher educational attainment is associated with lower levels of isolation.

Gender and Cohort Differences in Social Isolation

Tables 2.5A and 2.5B display results for MIDUS and HRS, respectively, adding cohort and gender as time-invariant covariates predicting the latent intercept as well as isolation at the first age group (25-29 for MIDUS and 50-52 for HRS) to the best fitting longitudinal model. Results in both MIDUS (coefficient(coef.) = 0.04; $p = 0.001$) and HRS (coef. = 0.06; $p = <0.001$) suggests that more recent birth cohorts have higher latent intercepts compared to earlier birth cohorts. In the ALT Intercept Only Model, the latent intercept captures time-invariant factors that influence social isolation. Therefore, these findings suggest that more recent cohorts have higher levels of time-invariant factors that influence social isolation. This differs from my hypothesis and finding in empirical Chapter One which showed no significant cohort differences in social isolation. However, in this context, the latent intercept has little substantive meaning.

Examining gender differences, I find that men are more isolated than women at the first age group (25-29) of MIDUS (coef. = -0.22; p = <0.001), but there are no significant gender differences in the latent intercept (p = 0.793). Meanwhile in HRS, while men are more isolated than women at the first age group (50-52) (coef. = -0.12; p = 0.042), women have higher levels of social isolation than men at the latent intercept (coef. = 0.04; p = <0.001). Since the best fitting model of social isolation was the ALT Intercept Only Model, which does not include a slope factor I did not estimate cohort or gender differences in the slope. My results partially support my hypothesis that men will have higher mean levels of isolation than women. Men had higher mean levels of isolation in the first age group than women in both MIDUS and HRS. Yet, cohort and gender only explained about one percent of the variability in the latent intercept of social isolation in both MIDUS and HRS.

Next, I fit models adding gender and cohort as direct covariates on social isolation to test whether cohort and gender differences in social isolation vary by age (Tables 2.6A and 2.6B). In MIDUS, there was conflicting evidence in the model fit statistics as to which model fit the data the best. However, investigating the fit statistics and model results, I determined a model with equality constraints for gender, but not cohort was the best model (Model B). While a model incorporating equality constraints for cohort by age provided a better BIC, this model had lower CFI, TLI, and RMSEA values. Given these results I chose not to restrict the effects of cohort to be equal by age to be more conservative. Compared to previous estimates in MIDUS, I similarly find no gender differences in social isolation (Table 2.7A). Additionally, results indicate that more recent birth cohorts are more isolated, with the magnitude of this relationship appearing to be stronger at older ages. For example, for ages 30-34, birth cohort was not significantly related to social isolation. However, this relationship became significant for the 45-49 age group (coef. = 0.04; p = 0.047) and increased in magnitude to 0.25 (p = 0.010) by ages 80 and older.

Meanwhile, results from HRS suggest that a model which constrained the effect of cohort, but not gender to be equal by age fit the data the best (Table 2.6B). More recent birth cohorts had higher levels of isolation than earlier cohorts, with the magnitude of this relationship remaining stable with age (Table 2.7B; coef. = 0.09; p = <0.001). My hypothesis that the relationship between social isolation and cohort does not differ by age is supported by the HRS results, but not by the MIDUS results. Given the younger age range of MIDUS respondents, this may suggest that cohort differences in isolation may not develop until mid- or late-life.

Gender results in HRS indicate that men are more isolated than women in late midlife (coef. = -0.07; p = 0.005), with disparities narrowing with age and reversing around age 75 (coef. = 0.08; p = <0.001) with women becoming more isolated than men (coef. = 0.69; p = <0.001 at ages 89+). These findings on gender differences in isolation mirror the findings from the previous empirical chapter and support my hypothesis on the relationship between social isolation and gender with age.

Variations in Longitudinal Models of Social Isolation with the Inclusion or Exclusion of Relationship Status

Given the results from the previous empirical chapter, which finds that the direction of gender differences in social isolation varies by the inclusion or exclusion of relationship status, I ran longitudinal analyses excluding relationship status from the social isolation index, thus creating a 3-item index. Tables 2.8A and 2.8B show that even when excluding relationship status from the social isolation index, the ALT Intercept Only Model is still the best fitting model in both MIDUS and HRS. The only difference is the ALT Intercept Only Model in HRS fits better with autoregressive coefficients constrained to be equal across age groups. Parameter estimates for the models which include gender and cohort as covariates on the latent intercept and first age group are largely the same whether or not relationship status is included in the index (Table 2.9A and 2.9B). The main difference is in the association of gender with the latent intercept. In MIDUS, there are no gender differences in social isolation at ages 25-29 (coef. = -0.09; p = 0.329), but men are more isolated than women at the latent intercept (coef. = -0.10; p = <0.001). These significant levels are reversed when including relationship status in the social isolation index. In HRS, men are more isolated than women at ages 50-52 (coef. = -0.12; p = 0.044), in-line with previous findings including relationship status. However, when excluding relationship status from the social isolation index men, rather than women have higher latent intercepts (coef. = -0.14; p = <0.001). This suggests that when excluding relationship status from the social isolation index, men have higher levels of time-invariant factors that influence social isolation.

Similarly, models which include gender and cohort as direct covariates on social isolation find that model estimates remain largely the same whether including or excluding relationship status in the social isolation index, except for the gender results (Tables 2.10A and 2.10B). When including relationship status in the social isolation index there are no significant gender differences in MIDUS. However, when excluding relationship status, there are significant gender differences in social isolation, with men having higher levels of isolation than women (Table 2.11A). This gender difference remains consistent across all age groups. The results in HRS are similar, except for a convergence in gender differences around age 85, which is likely due to selective survival (Table 2.11B). These findings are similar to empirical Chapter One; that is, removing relationship status from the social isolation index shows that men are more consistently isolated than women across adulthood.

DISCUSSION

Empirical Chapter One showed that 14 percent of U.S. adults are socially isolated, a figure which has increased during the COVID-19 pandemic (Peng and Roth 2021; Quintana et al. 2021). This is concerning because social isolation has been linked to a wide range of detrimental outcomes, including premature mortality, higher healthcare spending, and a lack of social support (Flowers et al. 2017; Holt-Lunstad et al. 2010; Umberson et al. 2010). Therefore, it is important for researchers to better understand trajectories of social isolation in order to determine when to focus interventions. While research on this topic has used a variety of longitudinal model specifications to assess trajectories of social isolation, no studies have explicitly compared fit across these models (Caspi et al. 2006; Umberson et al. 2022; Yang et al. 2013).

I proposed five potential longitudinal models to describe the trajectory of social isolation: enduring, spontaneous, lagged effects, life course, and hybrid (Bollen and Gutin 2021). The enduring perspective suggests that social isolation is stable across the life course (Cornwell et al. 2021; Ertel et al. 2009; Holmes et al. 2012). Conversely, the spontaneous view emphasizes the importance of recent events occurring around the time when assessments of social isolation were made (Brissette et al. 2000). The lagged effects perspective views social isolation within the context of recent history (Victor et al. 2022). Meanwhile, the life course perspective recognizes the importance of critical transitions as individuals age and experience different circumstances throughout their lives (Elder and Shanahan 2006; Shanahan 2000). Last, these perspectives are not mutually exclusive, and could be operating simultaneously.

Determining the best fitting longitudinal model is important for producing an accurate and unbiased understanding of social isolation. Additional gaps exist in how social isolation varies by factors such as cohort and gender. This chapter addresses these gaps by testing various longitudinal models of social isolation across adults aged 25 and older using data from MIDUS and HRS, respectively. I also examine cohort and gender differences in mean levels of isolation and rates of change of social isolation as well as whether cohort and gender differences in social isolation vary by age. Here, I highlight the three key findings of the chapter.

First, a hybrid model with both enduring and lagged effects (ALT Intercept Only Model) best fits the longitudinal trajectory of social isolation as individuals age from young adulthood to late life. This implies that there is relative stability in social isolation as individuals age through adulthood, due to both time-invariant factors as well as recent history. These results differ from the descriptive results in the previous empirical chapter, which found increases in social isolation with age. This is because the ALT Intercept Only Model accounts for random intercepts and lagged effects, which are difficult to capture in descriptive analyses; when doing so, an age trend is no longer evident. Additionally, this chapter analyzed within-person changes in social isolation, which may be different from the population-based estimates from the previous empirical chapter due to factors such as the varying composition of cohorts and different age groupings. Social connections may already be established by mid- and late-life, which could be leading to the path dependence of social isolation. For example, people may be married, have a specific group of friends, and/or be a part of particular social groups. These social ties may remain largely unchanged from one life stage to the next.

While this analysis did not test the mechanisms which lead to enduring levels of social isolation, past research has suggested this could be due to several reasons. First, continuity theory posits that adults try to preserve their ties to existing structures, such as social ties, as they age (Atchley 1989; Lynch et al. 2015). Literature has found that after critical life transitions, such as spousal bereavement or retirement, individuals become more active in other types of social participation to maintain their connectedness (Cornwell et al. 2008; Donnelly and Hinterlong 2010). Second, personality may play a role in social isolation, with introverts potentially being less likely to have large social networks and participate in group activities than extroverts. Third, stable self-perceptions, such as being a loner, may contribute to consistent levels of engagement in social interactions. Fourth, literature has found some evidence that brain structure may affect functioning in social domains, including social connections with others (Holmes et al. 2012; Kagan and Snidman 2004). These and other time-invariant aspects may be contributing to relative stability in social isolation across adulthood; future research is needed to determine what is leading to these enduring aspects.

Second, I found that more recent birth cohorts have higher levels of social isolation than earlier cohorts, with the magnitude of this relationship appearing to be stronger in older adulthood than midlife. This is consistent with results from my previous chapter which found significant cohort differences in social isolation. The direction of these findings are similar to Chapter One findings in MIDUS, and help resolve some of the mixed findings found in the HRS results from the previous chapter. Difference in findings from the HRS results in this chapter and the previous chapter could be due to the data and methods used as well as differences in missing data strategies. First, in this chapter I use more advanced analytic techniques that calculate random intercepts of social isolation, controlling for race/ethnicity and educational attainment. Meanwhile, in the previous chapter, I compare population means in the observed data. Second, in this chapter I use full information maximum likelihood to account for missing data, rather than using listwise deletion. These more robust methods and missing data strategies help provide more accurate estimates of the relationship between birth cohort and social isolation.

These findings are in line with previous literature which also found higher levels of social isolation in more recent birth cohorts (Parigi and Henson 2014; Putnam 2000). The increases in social isolation in more recent cohorts has been attributed to increased use of technology, declining trust in institutions, and other demographic trends (Margolis and Verdery 2017; Parigi and Henson 2014; Putnam 2000; Schwadel 2011). Although these factors could be leading to increases in social isolation for more recent cohorts, results indicate that cohort differences do not explain much variability in the latent intercept of social isolation. Therefore, research should further examine time-invariant aspects that could be leading to differences in social isolation between people.

Third, results suggest there are gender differences in social isolation, which varies by study. In MIDUS, there are no gender differences in social isolation. Meanwhile in HRS men are more isolated than women in late midlife, with these disparities narrowing and eventually reversing with age, with women becoming more isolated than men. This finding parallels results from my previous empirical chapter as well as work by Umberson and colleagues (2022). In the United States, men are socialized to be self-reliant and express emotional control which may lead to higher levels of social isolation for men than women at younger ages (Courtenay 2000; Umberson et al. 2014; Williams 2008). However, as individuals age, women are more likely to experience widowhood than men, leading to steeper increases in social isolation in late life than men (Mayol-García et al. 2021).

Further analyses taking relationship status out of the social isolation index suggest that men are more isolated than women at all stages of the life course, except in late life. During late life, gender differences dissipate, which is likely due to selective survival. These findings are similar to findings from my previous empirical chapter. Overall, results indicate that the inclusion or exclusion of relationship status in the social isolation index has key implications for understanding gender disparities in social isolation.

Implications

These findings have implications for both policy and future research. The stability of social isolation across adulthood implies the need to focus research earlier in the life course to determine if social isolation is more malleable earlier in life, such as in adolescence and the transition to adulthood. If there is evidence of changes in social isolation earlier in the life course, programs and policies should focus on these age groups to prevent persistent isolation. Additionally, these findings support the use of the ALT Intercept Only Model in trajectory analysis of social isolation. While literature has often used Growth Curve Models to assess social isolation, my results suggest this modeling strategy may not be the best fitting longitudinal structure of social isolation.

This chapter found both gender and cohort differences in social isolation. Higher levels of isolation in more recent cohorts may indicate a higher burden of isolation in the United States in the coming years. These trends coupled with the lasting impacts of the COVID-19 pandemic necessitate coordination and resource allocation to prepare for the continued and likely increased need for services to address isolation. Additionally, more research is needed to determine mechanisms behind these cohort differences. For example, are more recent cohorts more isolated because of technological changes, declining trust in institutions, demographic trends, or some other factor(s) (Parigi and Henson 2014)? Determining underlying causes can help better understand and address differences in isolation by cohort. Similarly, the varying trends in social isolation by gender warrant further attention. In particular, future research should investigate what aspects of isolation are most salient for men versus women and at which points in the life course.

However, I find that gender and cohort did not predict much of the variance in the latent intercept of social isolation. Therefore, more research should be done to examine what factors contribute to differences in time-invariant aspects of isolation. As mentioned previously, self-perceptions and personality could be potential mechanisms leading to differences in social isolation between people. Once these factors are better understood, research is needed to establish strategies to address them.

Limitations

As in the previous empirical chapter, the analyses in this chapter are limited with regard to the measurement tools used, the dichotomous coding of gender, and data limitations (for a more detailed description of these limitations please refer to the Limitations section in the previous empirical chapter). While this analysis used better analytic strategies to help address the confounding of age, period, and cohort effects than the previous chapter, these strategies still may not completely disentangle these effects. First, in examining how cohort predicts the random intercept of isolation, I am better able to disentangle the effects of age and cohort, because cohort and age are not linear and additive at the same level of analysis (Yang and Land 2013). Second, when examining whether cohort differences in social isolation vary by age, I examine cohort change within age groups which may reduce confounding; yet, it is unknown how well this strategy disentangles these effects. While previous literature has documented the effectiveness of strategies such as accounting and mixed models, there has been a dearth of literature examining age, period, and cohort effects within the structural equation modeling framework (Yang and Land 2013).

While restructuring the data to be focused on age instead of wave-based time made more theoretical sense for the research questions I was trying to answer and allowed me to have more assessment points, it resulted in several limitations. First, this restructuring resulted in a large amount of missing data. Although I used full information maximum likelihood (FIML) to account for missing data, FIML-based estimates could be affected by model misspecification and missing data patterns, thus biasing the estimates (Lee and Shi 2021). Second, some models did not converge due to model complexity and missing data. However as posited earlier, the ALT Intercept Only Model was determined to be the best fitting model, even among the models that did not converge, due to substantive evidence as well as from comparisons across models that did converge. Third, the analyses were unweighted because of the complexities of weighting with the model structure and amount of missing data. To help account for this, I included measures that were utilized to calculate the weights, as well as multiple sensitivity analyses including and excluding different controls, to help account for selection bias in sampling.

Conclusion

In conclusion, this chapter examined trajectories of social isolation from young adulthood to late life using two nationally representative samples of U.S adults. The findings suggest that social isolation is relatively stable within people as they age through adulthood, which is due to both time-invariant factors as well as recent history. Additionally, I found that there are cohort and gender differences in social isolation. More recent birth cohorts have higher levels of social isolation. I also found that while men are more isolated than women in earlier adulthood, these disparities converge and reverse at later ages with women becoming more isolated than men. Yet, cohort and gender differences explain only a small amount of variation in the time-invariant factors affecting social isolation. Therefore, future research is needed to determine which factors better explain these variations and how they can be addressed.

TABLES AND FIGURES

Figure 2.1. Proposed longitudinal models

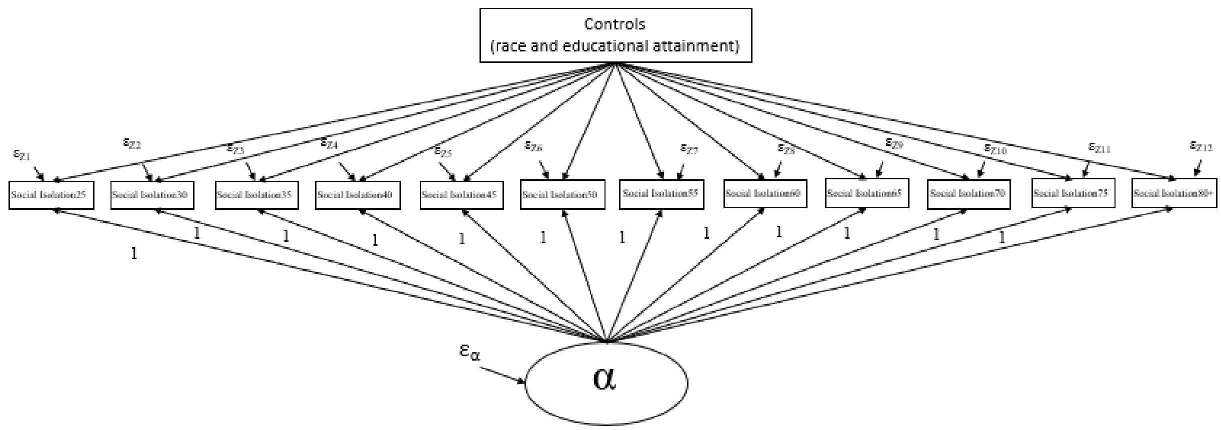
α = latent intercept

β = latent slope

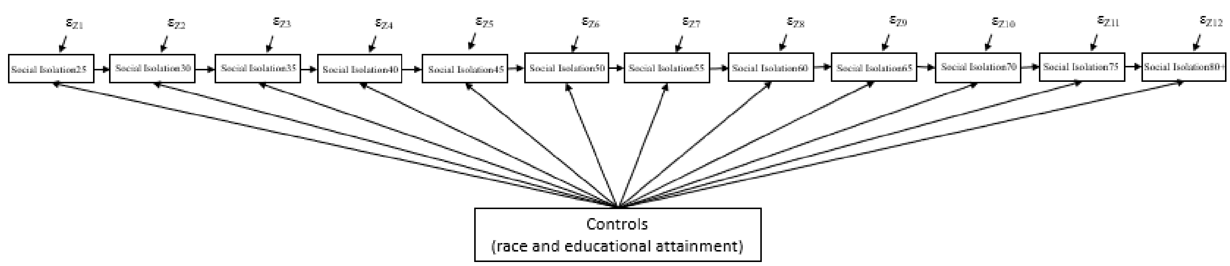
Social Isolation$_j$ =Social isolation index at Age $_j$

j = 25-29, 30-34, 35-39, 40-44, 45-49, 50-54, 55-59, 60-64, 65-69, 70-74, 75-79, 80+[3]

A. Time-Invariant (Enduring) Model

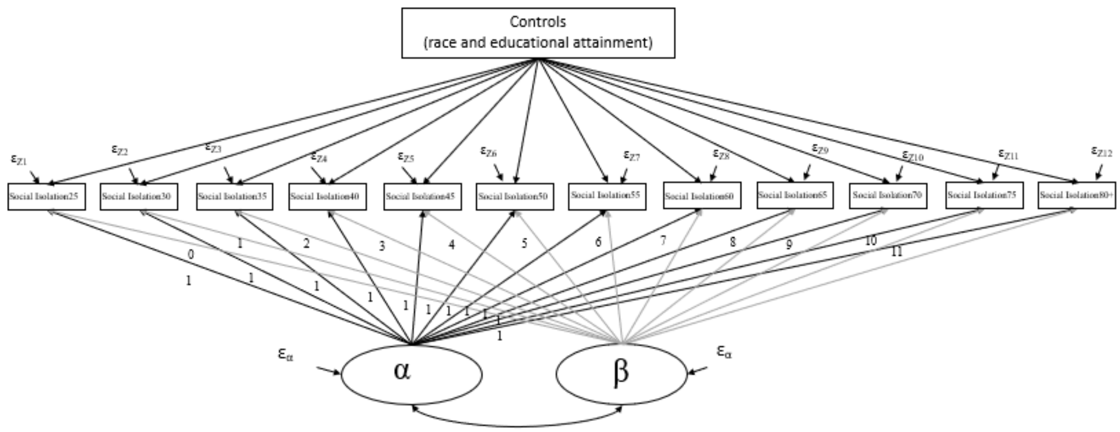


B. Autoregressive (Lagged Effects) Model

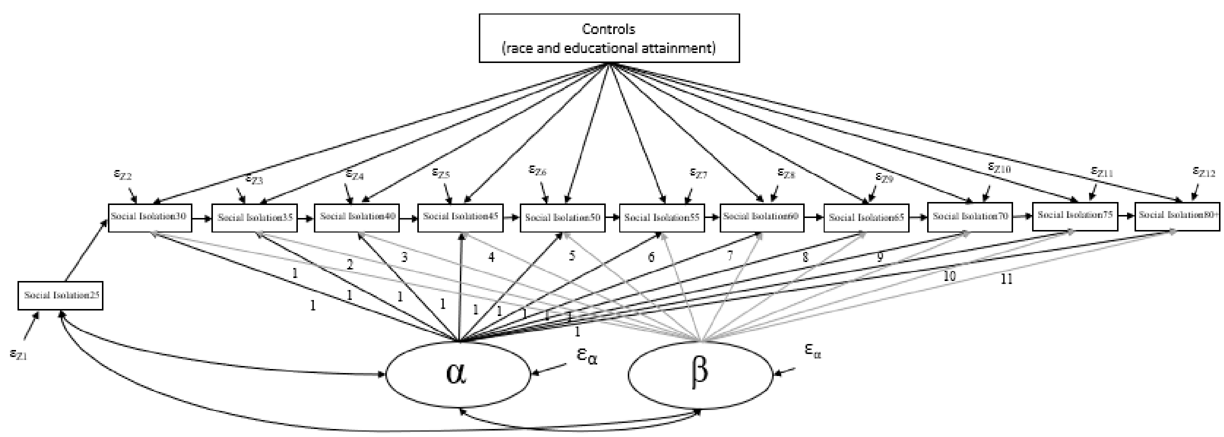


C. Growth Curve (Life Course) Model

[3] Example given for MIDUS. HRS has the same proposed models, with j = 50-52, 53-55, 56-58, 59-61, 62-64, 65-67, 68-70, 71-73, 74-76, 77-79, 80-82, 83-85, 86-88, 89+



D. Autoregressive Latent Trajectory Growth (Hybrid) Model



E. Autoregressive Latent Trajectory Intercept Only (Hybrid) Model

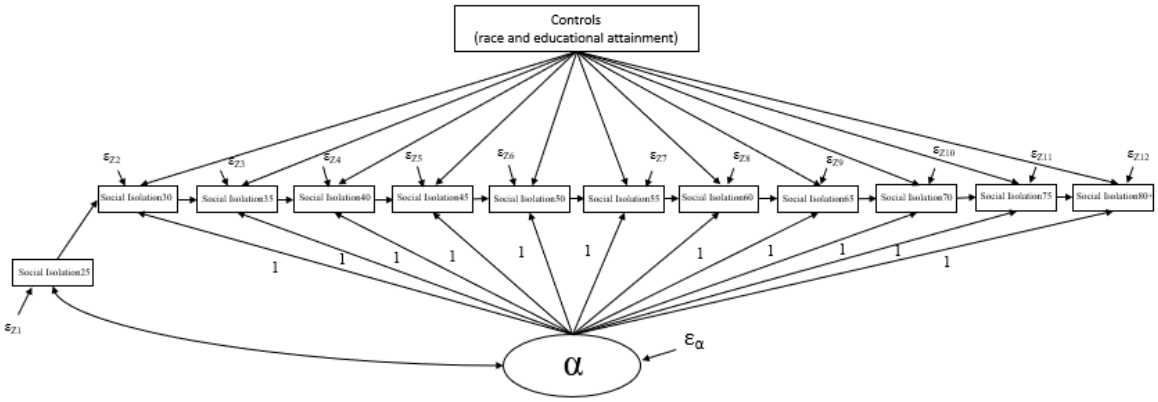


Table 2.1. Example of data structure based on age instead of waves

	Age											
Example ID	25-29	30-34	35-39	40-44	45-49	50-54	55-59	60-64	65-69	70-74	75-79	80+
1	X	.	X	X	.	.	.	.	.	.	.	.
2	.	.	X	.	X	.	X	.	.	.	.	.
3	.	.	.	X	.	X	.	X	.	.	.	.
4	.	.	.	.	.	.	X	.	X	X	.	.
5	.	.	.	.	.	.	.	.	X	.	X	X

x = value for social isolation; . = missing

Table 2.2A. Weighted sample characteristics, National Survey of Midlife Development in the United States, 1995-2014 (N = 3,052)

Variables	Mean (SD) / Proportion
Social isolation index (0-4)	
25-29	1.42 (0.90)
30-34	1.24 (0.90)
35-39	1.19 (0.98)
40-44	1.17 (0.96)
45-49	1.24 (0.97)
50-54	1.27 (0.99)
55-59	1.22 (0.96)
60-64	1.22 (0.96)
65-69	1.20 (0.95)
70-74	1.19 (0.96)
75-79	1.15 (0.96)
80+	1.40 (1.02)
Women	0.53
Cohort	
1915-1924	0.06
1925-1934	0.13
1935-1944	0.16
1945-1954	0.24
1955-1964	0.28
1965-1974	0.12
Race/ethnicity	
Non-Hispanic White	0.81
Non-Hispanic Black	0.08
Hispanic	0.07
Non-Hispanic Other Races	0.04
Educational attainment	
Less than high school degree	0.11
High school degree	0.33
Some college	0.28
College degree or higher	0.28

Table 2.2B. Weighted sample characteristics, Health and Retirement Study, 2006-2016 (N = 24,501)

Variables	Mean (SD) / Proportion
Social isolation index (0-4)	
50-52	1.39 (0.98)
53-55	1.38 (1.02)
56-58	1.42 (1.03)
59-61	1.43 (1.04)
62-64	1.45 (1.03)
65-67	1.42 (1.05)
68-70	1.40 (1.03)
71-73	1.39 (1.06)
74-76	1.42 (1.07)
77-79	1.46 (1.05)
80-82	1.59 (1.08)
83-85	1.67 (1.05)
86-88	1.86 (1.05)
89+	2.13 (1.00)
Women	0.53
Cohort	
1915-1924	0.06
1925-1934	0.12
1935-1944	0.20
1945-1954	0.35
1955-1964	0.27
Race/ethnicity	
Non-Hispanic White	0.75
Non-Hispanic Black	0.11
Hispanic	0.10
Non-Hispanic Other Races	0.04
Educational attainment	
Less than high school degree	0.17
High school degree	0.30
Some college	0.25
College degree or higher	0.28

Table 2.3A. Comparison of fit statistics for the National Survey of Midlife Development in the United States, 1995-2014 (N = 3,052)

Model	x^2	DF	BIC	CFI	TLI	RMSEA
Latent Time-Invariant	149.84	87	-587.15	0.969	0.950	0.013
Autoregressive (AR Constrained)	243.07	75	-438.95	0.924	0.861	0.022
Autoregressive	244.46	65	-364.29	0.922	0.835	0.024
Linear Growth Curve	133.48	84	-574.53	0.975	0.959	0.012
ALT Intercept Only (AR Constrained)	115.17	89	-631.27	0.987	0.980	0.008
ALT Intercept Only	108.58	79	-559.51	0.986	0.976	0.009

Notes: Full informational maximum likelihood was used to account for missing data. Models were run with robust maximum likelihood, controlled for race and educational attainment, and social isolation variances were constrained to equal by age. ALT Growth Model did not converge. AR = autoregressive equation, ALT = autoregressive latent trajectory.

Table 2.3B. Comparison of fit statistics for the Health and Retirement Study, 2006-2016 (N = 24,501)

Model	x^2	DF	BIC	CFI	TLI	RMSEA
Latent Time-Invariant	1075.17	116	-461.28	0.965	0.947	0.015
Autoregressive (AR Constrained)	3065.83	103	723.06	0.905	0.839	0.026
Autoregressive	3196.68	91	719.55	0.912	0.830	0.027
Linear Growth Curve	935.73	113	-548.40	0.971	0.966	0.014
ALT Intercept Only (AR Constrained)	981.56	118	-544.21	0.968	0.953	0.014
ALT Intercept Only	828.80	106	-560.12	0.975	0.959	0.013

Notes: Full informational maximum likelihood was used to account for missing data. Models were run with robust maximum likelihood, controlled for race and educational attainment, and social isolation variances were constrained to equal by age. ALT Growth Model did not converge. Linear Growth Curve Model only converged with education covariates. AR = autoregressive equation, ALT = autoregressive latent trajectory.

Table 2.4A. Select parameter estimates from the Autoregressive Latent Trajectory Intercept Only Model, National Survey of Midlife Development in the United States, 1995-2014 (N = 3,052)

Parameter	Estimate	Std. Err.	P-value
Autoregressives (with all coefficients equal)			
$SI_t \sim SI_{t-1}$	0.313	0.077	<0.001
Intercept			
Latent time-invariant	0.916	0.106	<0.001
Mean			
SI 25	1.442	0.052	<0.001
Covariances			
Intercept ~~ SI 25	0.179	0.050	<0.001
Variances			
SI_t (constrained to equal across $_t$)	0.377	0.013	<0.001
SI 25	0.801	0.055	<0.001
Intercept	0.234	0.064	<0.001
R-square			
SI 80	0.616		
SI 75	0.608		
SI 70	0.603		
SI 65	0.597		
SI 60	0.603		
SI 55	0.604		
SI 50	0.611		
SI 45	0.621		
SI 40	0.608		
SI 35	0.595		
SI 30	0.553		

Notes: Full informational maximum likelihood was used to account for missing data. Models were run with robust maximum likelihood and controlled for race and educational attainment.
x^2 = 115; DF = 89; BIC = -631.27; CFI = 0.987; TLI = 0.980; RMSEA = 0.008
SI = social isolation; t = 30-34, 35-39, 40-44, 45-49, 50-54, 55-59, 60-64, 65-69, 70-74, 75-79, 80+

Table 2.4B. Select parameter estimates from the Autoregressive Latent Trajectory Intercept Only Model, Health and Retirement Study, 2006-2016 (N = 24,501)

Parameter	Estimate	Std. Err.	P-value
Autoregressives			
SI 89 ~ SI 86	0.309	0.025	<0.001
SI 86 ~ SI 83	0.235	0.026	<0.001
SI 83 ~ SI 80	0.201	0.023	<0.001
SI 80 ~ SI 77	0.185	0.023	<0.001
SI 77 ~ SI 74	0.148	0.021	<0.001
SI 74 ~ SI 71	0.157	0.021	<0.001
SI 71 ~ SI 68	0.145	0.021	<0.001
SI 68 ~ SI 65	0.113	0.021	<0.001
SI 65 ~ SI 62	0.141	0.021	<0.001
SI 62 ~ SI 59	0.120	0.021	<0.001
SI 59 ~ SI 56	0.136	0.021	<0.001
SI 56 ~ SI 53	0.140	0.021	<0.001
SI 53 ~ SI 50	0.124	0.024	<0.001
Intercept			
Latent time-invariant	1.305	0.031	<0.001
Mean			
SI 50	1.385	0.028	0.020
Covariances			
Intercept ~~ SI 50	0.531	0.034	<0.001
Variances			
SI_t (constrained to equal across $_t$)	0.401	0.006	<0.001
SI 50	1.023	0.042	<0.001
Intercept	0.463	0.025	<0.001
R-square			
SI 89	0.721		
SI 86	0.682		
SI 83	0.665		
SI 80	0.655		
SI 77	0.636		
SI 74	0.640		
SI 71	0.629		
SI 68	0.612		
SI 65	0.624		
SI 62	0.616		
SI 59	0.622		
SI 56	0.626		
SI 53	0.615		

Notes: Full informational maximum likelihood was used to account for missing data. Models were run with robust maximum likelihood and controlled for race and educational attainment.
x^2 = 829 DF = 106; BIC = -560.12; CFI = 0.975; TLI = 0.959; RMSEA = 0.013
SI = social isolation; t = 53-55, 56-58, 59-61, 62-64, 65-67, 68-70, 71-73, 74-76, 77-79, 80-82, 83-85, 86-88, 89+

Table 2.5A. Select parameter estimates from the Autoregressive Latent Trajectory Intercept Only Model adding gender and cohort as predictors on growth parameters, National Survey of Midlife Development in the United States, 1995-2014 (N = 3,052)

Parameter	Estimate	Std. Err.	P-value
Autoregressives (with all coefficients equal)			
SI_t ~ SI_{t-1}	0.309	0.082	<0.001
Regressions			
Intercept ~ cohort	0.038	0.012	0.001
Intercept ~ women	-0.006	0.024	0.793
SI 25 ~ cohort	-0.194	0.286	0.498
SI 25 ~ women	-0.221	0.099	0.026
Intercept			
Latent time-invariant	0.828	0.106	<0.001
Mean			
SI 25	2.521	1.424	0.077
Covariances			
Intercept ~~ SI 25	0.173	0.050	0.001
Variances			
SI_t (constrained to equal across $_t$)	0.377	0.013	<0.001
SI 25	0.801	0.055	<0.001
Intercept	0.234	0.064	<0.001
R-square			
SI 80	0.619		
SI 75	0.610		
SI 70	0.605		
SI 65	0.600		
SI 60	0.605		
SI 55	0.605		
SI 50	0.613		
SI 45	0.622		
SI 40	0.609		
SI 35	0.595		
SI 30	0.555		
SI 25	0.093		
Intercept	0.012		

Notes: Full informational maximum likelihood was used to account for missing data. Models were run with robust maximum likelihood and controlled for race and educational attainment.
x^2 = 165; DF = 109; BIC = -750.21; CFI = 0.972; TLI = 0.959; RMSEA = 0.011
SI = social isolation; t = 30-34, 35-39, 40-44, 45-49, 50-54, 55-59, 60-64, 65-69, 70-74, 75-79, 80+

Table 2.5B. Select parameter estimates from the Autoregressive Latent Trajectory Intercept Only Model adding gender and cohort as predictors on growth parameters, Health and Retirement Study, 2006-2016 (N = 24,501)

Parameter	Estimate	Std. Err.	P-value
Autoregressives			
SI 89 ~ SI 86	0.334	0.025	<0.001
SI 86 ~ SI 83	0.259	0.026	<0.001
SI 83 ~ SI 80	0.224	0.023	<0.001
SI 80 ~ SI 77	0.202	0.023	<0.001
SI 77 ~ SI 74	0.162	0.021	<0.001
SI 74 ~ SI 71	0.167	0.022	<0.001
SI 71 ~ SI 68	0.152	0.021	<0.001
SI 68 ~ SI 65	0.116	0.021	<0.001
SI 65 ~ SI 62	0.141	0.021	<0.001
SI 62 ~ SI 59	0.115	0.021	<0.001
SI 59 ~ SI 56	0.128	0.021	<0.001
SI 56 ~ SI 53	0.128	0.022	<0.001
SI 53 ~ SI 50	0.110	0.024	<0.001
Regressions			
Intercept ~ cohort	0.063	0.007	<0.001
Intercept ~ women	0.038	0.011	<0.001
SI 50 ~ cohort	0.193	0.080	0.016
SI 50 ~ women	-0.116	0.057	0.042
Intercept			
Latent time-invariant	1.144	0.032	<0.001
Mean			
SI 50	0.728	0.312	0.020
Covariances			
Intercept ~~ SI 50	0.537	0.032	<0.001
Variances			
SI_t (constrained to equal across $_t$)	0.400	0.006	<0.001
SI 50	1.022	0.041	<0.001
Intercept	0.461	0.026	<0.001
R-square			
SI 89	0.740		
SI 86	0.700		
SI 83	0.680		
SI 80	0.666		
SI 77	0.645		
SI 74	0.646		
SI 71	0.634		

SI 68	0.615
SI 65	0.625
SI 62	0.614
SI 59	0.619
SI 56	0.621
SI 53	0.611
SI 50	0.054
Intercept	0.013

Notes: Full informational maximum likelihood was used to account for missing data. Models were run with robust maximum likelihood and controlled for race and educational attainment.
x^2 = 1316 DF = 130; BIC = -452.56; CFI = 0.958; TLI = 0.934; RMSEA = 0.016
SI = social isolation; t = 53-55, 56-58, 59-61, 62-64, 65-67, 68-70, 71-73, 74-76, 77-79, 80-82, 83-85, 86-88, 89+

Table 2.6A. Comparison of fit statistics for models adding gender and cohort as direct covariates on social isolation, the National Survey of Midlife Development in the United States, 1995-2014 (N = 3,052)

Model	x^2	DF	BIC	CFI	TLI	RMSEA	Model Comparison	x2 Difference Test
A: Direct controls of cohort and gender on SI	130.53	91	-638.84	0.982	0.968	0.010		
B: Model A + Equality constraints for gender by age	140.61	101	-706.96	0.981	0.969	0.010	B vs. A	0.327
C: Model A + Equality constraints for cohort by age	147.13	101	-702.56	0.978	0.964	0.010	C vs. A	0.101
D: Model C + Equality constraints for gender by age	170.73	111	-760.88	0.970	0.957	0.012	D vs. C	0.020

Notes: Full informational maximum likelihood was used to account for missing data. Models were run with robust maximum likelihood, controlled for race and education, and social isolation variances were constrained to equal by age.

Table 2.6B. Comparison of fit statistics for models adding gender and cohort as direct covariates on social isolation, Health and Retirement Study, 2006-2016 (N = 24,501)

Model	x2	DF	BIC	CFI	TLI	RMSEA	Model Comparison	x2 Difference Test
A: Direct controls of cohort and gender on SI	794.78	108	-400.24	0.978	0.959	0.012		
B: Model A + Equality constraints for gender by age	1248.62	120	-176.79	0.962	0.935	0.016	B vs. A	<0.001
C: Model A + Equality constraints for cohort by age	823.11	120	-449.09	0.976	0.960	0.012	C vs. A	<0.001
D: Model C + Equality constraints for gender by age	1320.78	132	-187.43	0.958	0.935	0.016	D vs. C	<0.001

Notes: Full informational maximum likelihood was used to account for missing data. Models were run with robust maximum likelihood, controlled for race and education, and social isolation variances were constrained to equal by age.

SI = social isolation

Table 2.7A. Select parameter estimates from the Autoregressive Latent Trajectory Intercept Only Model adding gender and cohort as direct covariates on social isolation, National Survey of Midlife Development in the United States, 1995-2014 (N = 3,052)

Parameter	Estimate	Std. Err.	P-value
Autoregressives (with all coefficients equal)			
SI_t ~ SI_{t-1}	0.309	0.079	<0.001
Regressions			
SI_t ~ Women	-0.010	0.023	0.681
SI 80 ~ Cohort	0.250	0.096	0.010
SI 75 ~ Cohort	0.041	0.062	0.508
SI 70 ~ Cohort	0.149	0.038	<0.001
SI 65 ~ Cohort	0.031	0.030	0.293
SI 60 ~ Cohort	0.083	0.028	0.003
SI 55 ~ Cohort	0.057	0.024	0.018
SI 50 ~ Cohort	0.058	0.023	0.013
SI 45 ~ Cohort	0.039	0.020	0.047
SI 40 ~ Cohort	0.027	0.024	0.254
SI 35 ~ Cohort	-0.004	0.023	0.864
SI 30 ~ Cohort	0.016	0.025	0.522
Intercept			
Latent time-invariant	0.833	0.103	<0.001
Mean			
SI 25	1.459	0.053	<0.001
Covariances			
Intercept ~~ SI 25	0.179	0.050	<0.001
Variances			
SI_t (constrained to equal across $_t$)	0.373	0.013	<0.001
SI 25	0.820	0.056	<0.001
Intercept	0.235	0.062	<0.001
R-square			
SI 80	0.661		
SI 75	0.617		
SI 70	0.627		
SI 65	0.605		
SI 60	0.617		
SI 55	0.612		
SI 50	0.619		
SI 45	0.624		
SI 40	0.610		
SI 35	0.596		

SI 30	0.554

Notes: Full informational maximum likelihood was used to account for missing data. Models were run with robust maximum likelihood and controlled for race and educational attainment.

x2 = 141; DF = 101; BIC = -706.96; CFI = 0.981; TLI = 0.969; RMSEA = 0.010

SI = social isolation; t = 30-34, 35-39, 40-44, 45-49, 50-54, 55-59, 60-64, 65-69, 70-74, 75-79, 80+

Table 2.7B. Select parameter estimates from the Autoregressive Latent Trajectory Intercept Only Model adding gender and cohort as direct covariates on social isolation, Health and Retirement Study, 2006-2016 (N = 24,501)

Parameter	Estimate	Std. Err.	P-value
Autoregressives			
SI 89 ~ SI 86	0.185	0.028	<0.001
SI 86 ~ SI 83	0.174	0.027	<0.001
SI 83 ~ SI 80	0.170	0.024	<0.001
SI 80 ~ SI 77	0.158	0.023	<0.001
SI 77 ~ SI 74	0.132	0.021	<0.001
SI 74 ~ SI 71	0.146	0.021	<0.001
SI 71 ~ SI 68	0.146	0.021	<0.001
SI 68 ~ SI 65	0.108	0.021	<0.001
SI 65 ~ SI 62	0.134	0.021	<0.001
SI 62 ~ SI 59	0.105	0.021	<0.001
SI 59 ~ SI 56	0.112	0.021	<0.001
SI 56 ~ SI 53	0.112	0.021	<0.001
SI 53 ~ SI 50	0.091	0.023	<0.001
Regressions			
SI_t ~ Cohort	0.091	0.007	<0.001
SI 89 ~ Women	0.686	0.050	<0.001
SI 86 ~ Women	0.436	0.042	<0.001
SI 83 ~ Women	0.296	0.034	<0.001
SI 80 ~ Women	0.222	0.028	<0.001
SI 77 ~ Women	0.145	0.024	<0.001
SI 74 ~ Women	0.082	0.023	<0.001
SI 71 ~ Women	-0.009	0.021	0.668
SI 68 ~ Women	-0.018	0.022	0.400
SI 65 ~ Women	-0.045	0.021	0.035
SI 62 ~ Women	-0.049	0.021	0.021
SI 59 ~ Women	-0.029	0.021	0.168
SI 56 ~ Women	-0.049	0.021	0.018
SI 53 ~ Women	-0.067	0.024	0.005
Intercept			
Latent time-invariant	1.106	0.031	<0.001
Mean			
SI 50	1.410	0.028	<0.001
Covariances			
Intercept ~~ SI 50	0.551	0.033	<0.001
Variances			
SI_t (constrained to equal across $_t$)	0.392	0.005	<0.001

SI 50	1.027	0.042	<0.001
Intercept	0.492	0.026	<0.001
R-square			
SI 89	0.714		
SI 86	0.688		
SI 83	0.677		
SI 80	0.667		
SI 77	0.652		
SI 74	0.656		
SI 71	0.651		
SI 68	0.631		
SI 65	0.642		
SI 62	0.630		
SI 59	0.631		
SI 56	0.632		
SI 53	0.620		

Notes: Full informational maximum likelihood was used to account for missing data. Models were run with robust maximum likelihood and controlled for race and educational attainment.
x2 = 823 DF = 120; BIC = -449.09; CFI = 0.976; TLI = 0.960; RMSEA = 0.012
SI = social isolation; t = 53-55, 56-58, 59-61, 62-64, 65-67, 68-70, 71-73, 74-76, 77-79, 80-82, 83-85, 86-88, 89+

Table 2.8A. Comparison of fit statistics for models taking relationship status out of the isolation index, the National Survey of Midlife Development in the United States, 1995-2014 (N = 3,052)

Model	x2	DF	BIC	CFI	TLI	RMSEA
Latent Time-Invariant	158.96	87	-580.24	0.953	0.925	0.014
Autoregressive (AR Constrained)	205.31	75	-461.50	0.921	0.855	0.020
Autoregressive	190.33	65	-391.40	0.924	0.839	0.021
Linear Growth Curve	129.94	84	-577.10	0.970	0.950	0.012
ALT Intercept Only (AR Constrained)	142.18	89	-610.36	0.966	0.947	0.012
ALT Intercept Only	129.45	79	-542.21	0.968	0.945	0.012

Notes: Full informational maximum likelihood was used to account for missing data. Models were run with robust maximum likelihood, controlled for race and educational attainment, and social isolation variances were constrained to equal by age. ALT Growth Model did not converge. AR = autoregressive equation, ALT = autoregressive latent trajectory.

Table 2.8B. Comparison of fit statistics for models taking relationship status out of the isolation index, Health and Retirement Study, 2006-2016 (N = 24,501)

Model	x^2	DF	BIC	CFI	TLI	RMSEA
Latent Time-Invariant	559.51	116	-843.32	0.973	0.959	0.010
Autoregressive (AR Constrained)	2316.19	103	109.70	0.887	0.807	0.021
Autoregressive	2459.09	91	177.28	0.891	0.791	0.022
Linear Growth Curve	500.63	113	-848.96	0.975	0.971	0.009
ALT Intercept Only (AR Constrained)	566.42	118	-859.54	0.973	0.960	0.010
ALT Intercept Only	599.34	106	-746.01	0.972	0.954	0.010

Notes: Full informational maximum likelihood was used to account for missing data. Models were run with robust maximum likelihood, controlled for race and educational attainment, and social isolation variances were constrained to equal by age. ALT Growth Model did not converge. Linear Growth Curve Model only converged with race/ethnicity covariates. AR = autoregressive equation, ALT = autoregressive latent trajectory.

Table 2.9A. Select parameter estimates from the Autoregressive Latent Trajectory Intercept Only Model adding gender and cohort as predictors on growth parameters and excluding relationship status, National Survey of Midlife Development in the United States, 1995-2014 (N = 3,052)

Parameter	Estimate	Std. Err.	P-value
Autoregressives (with all coefficients equal)			
$SI_t \sim SI_{t-1}$	0.316	0.097	<0.001
Regressions			
Intercept ~ cohort	0.053	0.011	<0.001
Intercept ~ women	-0.093	0.023	<0.001
SI 25 ~ cohort	-0.458	0.290	0.115
SI 25 ~ women	-0.082	0.084	0.329
Intercept			
Latent time-invariant	0.716	0.108	<0.001
Mean			
SI 25	3.522	1.455	0.015
Covariances			
Intercept ~~ SI 25	0.104	0.042	0.014
Variances			
SI_t (constrained to equal across $_t$)	0.333	0.011	<0.001
SI 25	0.545	0.036	<0.001
Intercept	0.129	0.046	0.005
R-square			
SI 80	0.523		
SI 75	0.526		
SI 70	0.521		
SI 65	0.514		
SI 60	0.518		
SI 55	0.517		
SI 50	0.528		
SI 45	0.540		
SI 40	0.519		
SI 35	0.509		
SI 30	0.505		
SI 25	0.422		
Intercept	0.056		

Notes: Full informational maximum likelihood was used to account for missing data. Models were run with robust maximum likelihood and controlled for race and educational attainment.
x^2 = 172; DF = 109; BIC = -742.53; CFI = 0.960; TLI = 0.940; RMSEA = 0.014
SI = social isolation; t = 30-34, 35-39, 40-44, 45-49, 50-54, 55-59, 60-64, 65-69, 70-74, 75-79, 80+

Table 2.9B. Select parameter estimates from the Autoregressive Latent Trajectory Intercept Only Model adding gender and cohort and excluding relationship status, Health and Retirement Study, 2006-2016 (N = 24,501)

Parameter	Estimate	Std. Err.	P-value
Autoregressives (with all coefficients equal)			
SI_t ~ SI_{t-1}	0.103	0.022	<0.001
Regressions			
Intercept ~ cohort	0.087	0.006	<0.001
Intercept ~ women	-0.139	0.010	<0.001
SI 50 ~ cohort	0.028	0.076	0.714
SI 50 ~ women	-0.124	0.061	0.044
Intercept			
Latent time-invariant	0.979	0.029	<0.001
Mean			
SI 50	1.192	0.291	<0.001
Covariances			
Intercept ~~ SI 50	0.249	0.032	<0.001
Variances			
SI_t (constrained to equal across $_t$)	0.288	0.004	<0.001
SI 50	0.605	0.029	<0.001
Intercept	0.267	0.016	<0.001
R-square			
SI 89	0.576		
SI 86	0.567		
SI 83	0.566		
SI 80	0.567		
SI 77	0.561		
SI 74	0.563		
SI 71	0.564		
SI 68	0.565		
SI 65	0.563		
SI 62	0.564		
SI 59	0.562		
SI 56	0.564		
SI 53	0.555		
SI 50	0.008		
Intercept	0.057		

Notes: Full informational maximum likelihood was used to account for missing data. Models were run with robust maximum likelihood and controlled for race and educational attainment.
x^2 = 540, DF = 142; BIC = -1078.48; CFI = 0.974; TLI = 0.963; RMSEA = 0.011
SI = social isolation; t = 53-55, 56-58, 59-61, 62-64, 65-67, 68-70, 71-73, 74-76, 77-79, 80-82, 83-85, 86-88, 89+

Table 2.10A. Comparison of fit statistics for models adding gender and cohort as direct covariates on social isolation and taking relationship status out of the isolation index, the National Survey of Midlife Development in the United States, 1995-2014 (N = 3,052)

Model	x2	DF	BIC	CFI	TLI	RMSEA	Model Comparison	x2 Difference Test
A: Direct controls of cohort and gender on SI	152.35	91	-621.67	0.963	0.935	0.013		
B: Model A + Equality constraints for gender by age	160.92	101	-690.84	0.963	0.940	0.012	B vs. A	0.372
C: Model A + Equality constraints for cohort by age	168.59	101	-684.55	0.958	0.932	0.013	C vs. A	0.089
D: Model C + Equality constraints for gender by age	177.37	111	-754.47	0.957	0.938	0.012	D vs. C	0.397

Notes: Full informational maximum likelihood was used to account for missing data. Models were run with robust maximum likelihood, controlled for race and education, and social isolation variances were constrained to equal by age. ALT Growth Model did not converge.

SI = social isolation

Table 2.10B. Comparison of fit statistics for models adding gender and cohort as direct covariates on social isolation and taking relationship status out of the isolation index, Health and Retirement Study, 2006-2016 (N = 24,501)

Model	x2	DF	BIC	CFI	TLI	RMSEA	Model Comparison	x2 Difference Test
A: Direct controls of cohort and gender on SI	427.41	120	-707.85	0.982	0.969	0.008		
B: Model A + Equality constraints for gender by age	508.98	132	-736.90	0.976	0.964	0.009	B vs. A	<0.001
C: Model A + Equality constraints for cohort by age	457.27	132	-768.95	0.980	0.969	0.008	C vs. A	<0.001
D: Model C + Equality constraints for gender by age	542.63	144	-794.49	0.974	0.963	0.009	D vs. C	<0.001

Notes: Full informational maximum likelihood was used to account for missing data. Models were run with robust maximum likelihood, controlled for race and education, and social isolation variances were constrained to equal by age. ALT Growth Model did not converge.

SI = social isolation

Table 2.11A. Select parameter estimates from the Autoregressive Latent Trajectory Intercept Only Model adding gender and cohort as direct covariates on social isolation and excluding relationship status, National Survey of Midlife Development in the United States, 1995-2014 (N = 3,052)

Parameter	Estimate	Std. Err.	P-value
Autoregressives (with all coefficients equal)			
$SI_t \sim SI_{t-1}$	0.300	0.097	0.002
Regressions			
SIt ~ Women	-0.097	0.023	<0.001
SI 80 ~ Cohort	0.147	0.087	0.090
SI 75 ~ Cohort	0.091	0.054	0.091
SI 70 ~ Cohort	0.107	0.036	0.003
SI 65 ~ Cohort	0.057	0.029	0.054
SI 60 ~ Cohort	0.084	0.026	0.001
SI 55 ~ Cohort	0.069	0.023	0.002
SI 50 ~ Cohort	0.073	0.023	0.001
SI 45 ~ Cohort	0.069	0.019	<0.001
SI 40 ~ Cohort	0.030	0.022	0.173
SI 35 ~ Cohort	0.023	0.021	0.258
SI 30 ~ Cohort	0.051	0.024	0.030
Intercept			
Latent time-invariant	0.738	0.107	<0.001
Mean			
SI 25	1.214	0.044	<0.001
Covariances			
Intercept ~~ SI 25	0.114	0.044	0.010
Variances			
SI_t (constrained to equal across $_t$)	0.332	0.011	<0.001
SI 25	0.549	0.036	<0.001
Intercept	0.137	0.047	0.004
R-square			
SI 80	0.554		
SI 75	0.542		
SI 70	0.539		
SI 65	0.519		
SI 60	0.530		
SI 55	0.525		
SI 50	0.535		
SI 45	0.542		
SI 40	0.514		
SI 35	0.505		

SI 30	0.482

Notes: Full informational maximum likelihood was used to account for missing data. Models were run with robust maximum likelihood and controlled for race and educational attainment.

x2 = 161; DF = 101; BIC = -690.84; CFI = 0.963; TLI = 0.940; RMSEA = 0.012

SI = social isolation; t = 30-34, 35-39, 40-44, 45-49, 50-54, 55-59, 60-64, 65-69, 70-74, 75-79, 80+

Table 2.11B. Select parameter estimates from the Autoregressive Latent Trajectory Intercept Only Model adding gender and cohort as direct covariates on social isolation and excluding relationship status, Health and Retirement Study, 2006-2016 (N = 24,501)

Parameter	Estimate	Std. Err.	P-value
Autoregressives (with all coefficients equal)			
$SI_t \sim SI_{t-1}$	0.102	0.021	<0.001
Regressions			
SIt ~ Cohort	0.089	0.007	<0.001
SI 89 ~ Women	0.077	0.040	0.054
SI 86 ~ Women	-0.055	0.035	0.113
SI 83 ~ Women	-0.103	0.027	<0.001
SI 80 ~ Women	-0.142	0.024	<0.001
SI 77 ~ Women	-0.170	0.021	<0.001
SI 74 ~ Women	-0.157	0.020	<0.001
SI 71 ~ Women	-0.186	0.019	<0.001
SI 68 ~ Women	-0.191	0.020	<0.001
SI 65 ~ Women	-0.180	0.019	<0.001
SI 62 ~ Women	-0.166	0.019	<0.001
SI 59 ~ Women	-0.094	0.019	<0.001
SI 56 ~ Women	-0.089	0.020	<0.001
SI 53 ~ Women	-0.138	0.023	<0.001
Intercept			
Latent time-invariant	0.976	0.029	<0.001
Mean			
SI 50	1.229	0.030	<0.001
Covariances			
Intercept ~~ SI 50	0.248	0.031	<0.001
Variances			
SI_t (constrained to equal across $_t$)	0.287	0.004	<0.001
SI 50	0.609	0.029	<0.001
Intercept	0.268	0.016	<0.001
R-square			
SI 89	0.564		
SI 86	0.563		
SI 83	0.565		
SI 80	0.569		
SI 77	0.564		
SI 74	0.565		
SI 71	0.567		
SI 68	0.568		
SI 65	0.566		

SI 62	0.566
SI 59	0.563
SI 56	0.564
SI 53	0.556

Notes: Full informational maximum likelihood was used to account for missing data. Models were run with robust maximum likelihood and controlled for race and educational attainment.

x2 = 457 DF = 132; BIC = -768.95; CFI = 0.980; TLI = 0.969; RMSEA = 0.008

SI = social isolation; t = 53-55, 56-58, 59-61, 62-64, 65-67, 68-70, 71-73, 74-76, 77-79, 80-82, 83-85, 86-88, 89+

CHAPTER THREE. LINKAGES BETWEEN SOCIAL ISOLATION AND SELF-RATED HEALTH ACROSS ADULTHOOD

Over three decades of research has found that social relationships impact morbidity and mortality, with the magnitude of the effect being comparable or greater than other health risk factors such as smoking and physical activity (Holt-Lunstad et al. 2010; House et al. 1988; Pantell et al. 2013). Social isolation, in particular, has been associated with a wide range of health outcomes, including premature mortality, accelerated cognitive decline, cardiovascular disease, and higher allostatic load (Brummett et al. 2001; Cacioppo and Hawkley 2003; Cantarero-Prieto et al. 2018; Holt-Lunstad 2022; Holt-Lunstad et al. 2010; National Academies of Sciences, Engineering, and Medicine 2020). Although the connection between social isolation and health has been well-established, we know relatively little about how social isolation is associated with self-rated health across adulthood, or how this association varies by gender. I identify three gaps in the literature related to: 1) the age groups examined; 2) the reciprocal relationship between social isolation and self-rated health; and 3) differential health consequences of social isolation by gender.

First, most research to date linking social isolation to self-rated health, and other health outcomes, has been limited to older populations. While older adults are at an increased risk of isolation because they are more likely to experience the loss of family and friends and have physical and cognitive limitations (Cornwell and Waite 2009b; Holt-Lunstad et al. 2010; National Academies of Sciences, Engineering, and Medicine 2020), social isolation is likely a strong predictor of poor health across all of adulthood (Hämmig 2019). These findings suggest that research should expand the investigation of the social isolation-health association throughout adulthood (Valtorta and Hanratty 2012). Research on social isolation and health that takes a more expansive life course view could provide key information, such as whether social isolation confers more extensive health risks at certain ages compared with others.

Self-rated health is a key indicator to focus investigation of the social isolation-health association across adulthood for several reasons. First, self-rated health is an inclusive health measure that is frequently and consistently used in survey research (Au and Johnston 2014; Bollen and Gutin 2021; Jylhä 2009). It is also strongly predictive of mortality risk and is strongly related to the presence of chronic conditions (Dowd and Zajacova 2007; Idler and Benyamini 1997; Latham and Peek 2013; Mavaddat et al. 2014). Additionally, self-rated health is a key indicator of health at all stages of the life course, making it a useful measure for research which examines different stages of adulthood.

Second, while literature has largely focused on how social isolation is associated with poor health, there is a paucity of literature investigating the reciprocal relationship between these two concepts. Yet, research finds that those in poorer physical health are at a higher risk of social isolation (Ejiri et al. 2018; Iliffe et al. 2007; Kobayashi, Cloutier-Fisher, and Roth 2009; Robins et al. 2018). Ignoring the reciprocal relationship between social isolation and self-rated health does not fully capture how these concepts are related to each other across adulthood. Additionally, explicit modeling of the reciprocal relationship between social isolation and self-rated health would better account for the temporal ordering of exposure and outcome (Haas, Schaefer, and Kornienko 2010; Holt-Lunstad et al. 2010).

Third, literature has not adequately examined heterogeneity in the association between social isolation and self-rated health. Previous research as well as my previous empirical chapters have found gender differences in the prevalence of social isolation (Cornwell et al. 2008; Cudjoe et al. 2020; Krivo et al. 2013; Röhr et al. 2021; Vandervoort 2000), but has not examined whether social isolation confers more health risk for men or women. These findings would help determine at-risk populations for whom social isolation is particularly detrimental. Additionally, findings may suggest that social isolation is contributing to gender disparities in health.

To address these three gaps in the literature, this chapter examines the relationship between social isolation and self-rated health across adulthood. Additionally, I examine how the association between social isolation and self-rated health may differ by gender. These aims lead me to four research questions: First, how are social isolation and self-rated health prospectively related? Second, is there a reciprocal relationship between social isolation and self-rated health across adulthood? Third, does the magnitude of the association between social isolation and self-rated health vary by age? Fourth, how does the longitudinal association between social isolation and self-rated health vary by gender?

BACKGROUND

Relationship Between Social Isolation and Health

A wide range of literature has found that social isolation is detrimental for health, with a majority of the literature focusing on cardiovascular health and mortality (Barnes et al. 2022; Brummett et al. 2001; Everson-Rose and Lewis 2005; Hodgson et al. 2020; Holt-Lunstad et al. 2010). These studies have found that social isolation is associated with increased risk for fatal coronary heart disease, metabolic syndrome, and undiagnosed hypertension (Cené et al. 2023; Cornwell and Waite 2012; Eng et al. 2002; Yang et al. 2016; Yang, Boen, and Harris 2014; Yang et al. 2013). Additionally, those who are socially isolated have a 50 to 83 percent higher risk of premature mortality compared to those who are socially integrated (Berkman and Syme 1979; Steptoe et al. 2013; Yang et al. 2013).

While research on social isolation and its connections with cardiovascular health and mortality have been well established, a smaller amount of literature has examined how social isolation is associated with self-rated health. Self-rated health is a self-perceived measure that encompasses biological, social, and psychosocial aspects of health (Huisman and Deeg 2010; Jylhä 2009; Kaplan and Baron-Epel 2003). A conceptual framework developed by Jylhä (2009) describes self-rated health as an individual's cognitive assessment of their health which involves three steps. First, people identify various aspects of health, such as diagnoses, bodily sensations, and health behaviors. Next, individuals determine which of these aspects should be taken into consideration when evaluating their health. Lastly, people determine which level of the scale that is provided best fits their summary of their health. While other research suggests that this cognitive process may not be happening in a thoughtful, coordinated way and can be influenced by other factors such as mood, this conceptual framework provides a basis for the use of self-rated health within this chapter (Huisman and Deeg 2010).

Self-rated health is one of the most frequently and consistently used measures of health in survey research (Au and Johnston 2014; Bollen and Gutin 2021; Jylhä 2009). It is an inclusive health measure that is easy to administer, applicable to a wide range of ages, is strongly predictive of subsequent mortality risk, and is associated with multiple chronic conditions including coronary heart disease and diabetes (Dowd and Zajacova 2007; Idler and Benyamini 1997; Jylhä 2009; Latham and Peek 2013; Mavaddat et al. 2014). It also gives respondents the ability to evaluate and prioritize different aspects of their health with one simple question (Bombak 2013). How people think about their health can provide additional information on individuals' overall health as well as on other measures, such as health care utilization, than objective measures alone (Au and Johnston 2014; Jylhä 2009).

Research on social isolation and self-rated health has found that social isolation is associated with a 30 to 40 percent higher odds of reporting fair/poor health compared to those who are not isolated (Cornwell and Waite 2009b; Coyle and Dugan 2012; Iliffe et al. 2007; Luo and Li 2022). A 2019 article by Hämmig has been one of the few studies that has investigated the relationship between social isolation and self-rated health across a wide range of ages. Analyzing data on adolescents and adults aged 15 and older in the 2012 Swiss Health Survey, the author found that social isolation was associated with poorer self-rated health at all ages. Results also suggested a graded relationship between social isolation and self-rated health, where a higher level of social isolation was associated with higher odds of being in poor self-rated health. For example, Swiss residents who were highly isolated were five times more likely to report poor/fair self-rated health compared to those who were the most integrated. Meanwhile, those who were moderately isolated were three times more likely to have poor/fair self-rated health compared to those who were the most integrated. While the graded relationship was found in all four age groups, the social isolation-health relationship was strongest among adults aged 25 to 44, weakest among adults aged 65 and older, and moderate among adults aged 45 to 65. While this study provides key insights into the relationship between social isolation and self-rated health across a wide range of ages, longitudinal data is needed to better determine the temporal ordering of the association under question. Findings from previous literature lead me to hypothesize that:

> *Hypothesis 1:* Higher levels of social isolation will be associated with poorer self-rated health at all ages.

Mechanisms Linking Social Isolation and Self-Rated Health

Literature suggests three broad ways in which social relationships are linked to health: behavioral, psychosocial, and biological (Umberson and Montez 2010). These three broad mechanisms can be applied to the relationship between social isolation and self-rated health. First, social ties can influence health behavior. For example, spouses or friends can encourage people to stick to a diet, exercise, or adhere to medications (Berkman et al. 2000; Cornwell and Waite 2012; House et al. 1988). While not all social network influences are positive, as these same close others can encourage harmful health behaviors such as smoking and drug use, research suggests that having some social ties, even if not completely positive, are better than having no social ties (House 2001). Literature finds that being more socially connected, including being married, having children, and attending religious services is related to more positive health behaviors (Berkman et al. 2000; Denney 2010; Musick, House, and Williams 2004; Umberson 1987; Waite 1995). This is partially because being connected to others instills a sense of responsibility that lead individuals to engage in health promoting behaviors (Umberson and Montez 2010). Socially isolated individuals lack social ties which may promote positive health behaviors and in turn better self-rated health.

Second, psychosocial mechanisms such as social support, symbolic meanings and norms, and loneliness link social isolation to health (Thoits 2011). Social connections can provide access to multiple forms of support, including help with tasks, advice from others, a sense of being cared for, and needed resources such as money and transportation (House 2001; Shor, Roelfs, and Yogev 2013; Umberson et al. 2010), all of which can help reduce stress (Cohen 2004; Ditzen and Heinrichs 2014; Park et al. 2022; Pearlin 1989; Umberson et al. 2010). People who are socially isolated do not have access to these supports or resources. The absence of these stress-buffers may exacerbate the health consequences of stress. Similarly, symbolic meaning and norms may instill a greater sense of responsibility to stay healthy, which isolated people also do not have. For example, parents may be more motivated to maintain a healthy lifestyle to set an example for their children (Waite 1995). Lastly, social isolation can increase loneliness and depression symptoms, worsening self-reported health (Domènech-Abella et al. 2019; Hall-Lande et al. 2007; Teo et al. 2015).

Third, social isolation can directly influence biological processes. Social isolation can create chronic strain, leading to increased activation of the hypothalamic-pituitary-adrenal (HPA) axis and sympathetic nervous system (SNS; Cacioppo et al. 2015; Jackson et al. 2021; McEwen 1998; Seeman et al. 2002). The increased activation of the HPA axis and SNS over time can cause wear and tear on the body due to overworked biological systems. Dysregulation of cardiovascular, metabolic, and neuroendocrine processes can lead to increased inflammation, cortisol output, and blood pressure, all of which lead to poorer self-rated health (Eisenberger et al. 2017; Grant, Hamer, and Steptoe 2009; McCrory et al. 2016; Shankar et al. 2011). Additional research has found that social isolation can induce changes in gene expression, particularly in areas of the brain that are important for cognition, mood variations, and risk for addiction (Arzate-Mejía et al. 2020).

While I have primarily focused on how social isolation leads to worse health, poor health can also increase social isolation. Poor self-perceived health can be related to chronic conditions and functional limitations which may limit the ability for individuals to participate in social activities and engage with others (Sluzki 2010). For example, someone in poor health may spend a considerable amount of time managing their chronic conditions, face actual or perceived stigma against health conditions and statuses, be unable to leave their home, and face other challenges which may increase their isolation. In particular, research has found that having visual or hearing disabilities, functional limitations, chronic conditions, poorer self-rated health, or being hospitalized was associated with higher risk of social isolation (Coyle et al. 2017; Ejiri et al. 2018; Ha, Hougham, and Meltzer 2019; Jang et al. 2016; Kobayashi et al. 2009; Mick, Kawachi, and Lin 2014). Additionally, poor mental health can lead to social withdraw, thus increasing social isolation (Luo et al. 2012). These findings suggest it is important for researchers to investigate reciprocal relationships between social isolation and self-rated health. Exploring this reciprocal relationship not only helps researchers understand how social isolation and self-rated health are connected, but also has important implications for modeling. If the reciprocal relationships between social isolation and self-rated health are ignored, estimations of this relationship are biased leading to improper evidence on which to base interventions. Previous literature leads me to hypothesize:

> *Hypothesis 2:* There will be a reciprocal relationship between social isolation and self-rated health across adulthood, where higher social isolation will be associated with poorer self-rated health and poorer self-rated health will be associated with higher social isolation.

Social Isolation and Health Across Adulthood

Although the connection between social isolation and health has been well-established, gaps remain in how this association varies across adulthood. Research has found heterogeneity in both social isolation and self-rated health as individuals age. Throughout adulthood, people make assessments of their health and adjust and update these assessments based on new information (Huisman and Deeg 2010). This aligns with research which has found that self-rated health improves until young adulthood, after which it remains stable until beginning to decline with advancing age (McCullough and Laurenceau 2004; Sargent-Cox, Anstey, and Luszcz 2010;

Sokol et al. 2017). Meanwhile, research from my previous empirical chapters as well as other research finds that social isolation varies with age (Hämmig 2019; Umberson et al. 2022).

Given that social isolation and self-rated health both vary across the life span, the life course is a key framework for studying the association between these two concepts (Ben-Shlomo and Kuh 2002; Elder 1998; Elder et al. 2003; Teas et al. 2023; Umberson et al. 2010). A key component of the life course perspective is life span development, which is the idea that human development and aging are life-long processes (Elder 1998; Elder and Giele 2009; Elder et al. 2003). The principle of life span development highlights the importance of trajectories, which measure intraindividual stability and change in relationship to social and historical context (George 2009). This suggests that social isolation and self-rated health unfold together over the life course. While some studies have investigated the longitudinal association between social integration, which is the inverse of social isolation, or loneliness and health, these studies only used longitudinal data on measures of social integration (Cacioppo, Hawkley, and Thisted 2010; Yang et al. 2013) or health (Kobayashi and Steptoe 2018; Shartle et al. 2022). It is important to examine the longitudinal association in both social isolation and health to better understand how these factors unfold together.

Given that changes in social isolation and self-rated health occur across adulthood, it is important to identify the direction of the social isolation-health association. For example, do increases in social isolation lead to worse health, does poorer health lead to increases in isolation, or is there a reciprocal relationship between isolation and self-rated health? Initial research by Xiang and colleagues (2021) found a strong interrelationship between the trajectories of social isolation and dementia. These strong findings suggest the importance of investigating how trajectories of social isolation and health are related to each other.

Additionally, the magnitude of the association between social isolation and self-rated health may strengthen, weaken, or remain the same as individuals age. For example, some research has found that social isolation is more strongly related to poor health conditions and behaviors at younger than at older ages (Hämmig 2019). Literature on social integration, which is the inverse of social isolation, has found that integration is an important predictor of better metabolic and cardiovascular health in late adulthood, but not in midlife (Carmichael, Reis, and Duberstein 2015; Yang et al. 2016). However, more research is needed to determine when social isolation poses the greatest health risk during adulthood. While research has found conflicting findings regarding the magnitude of the association between social isolation and self-rated health by age, I hypothesize that social isolation will be particularly detrimental for the self-rated health of older adults who may already be experiencing poor health. The lack of social support and resources conferred from social connection to others may exacerbate declining health.

> *Hypothesis 3:* The magnitude of the association between social isolation and self-rated health will be stronger at older ages than younger ages.

Gender Differences in the Social Isolation-Health Association

Research has found varied evidence of gender disparities in social isolation. Some studies have found that women are more isolated than men, while others find that men are more isolated than women; still others have found no significant gender differences in social isolation (Cornwell et al. 2008; Cudjoe et al. 2020; Naito et al. 2021; Röhr et al. 2021; Steptoe et al. 2013; Vandervoort 2000). In analyses from my first and second empirical chapters, I found that men are more isolated than women in midlife, but that this gap narrows in older adulthood and reverses in late life, with women becoming more isolated than men. While this research has documented differences in levels of social isolation, it has not addressed if men or women experience greater health risks from social isolation.

Literature that has examined gender disparities in social isolation and health have found conflicting evidence. For example, Yang and colleagues (2013) found that social isolation was associated with greater risk of chronic inflammation and premature mortality in men compared to women. The authors suggest this is due to sex differences in physiology, in which stress reactivity is downregulated in women. The increased inflammatory response that socially isolated men experience likely contributes to their greater risk of premature mortality than socially isolated women. A recent analysis assessing the relationship between social isolation and cognitive function has similarly found that social isolation more strongly predicts poorer cognitive function in men than women, largely due to the mediating role of chronic inflammation (Qi, Ng, and Wu 2023). Meanwhile, other literature has found no reliable gender differences in the association between social isolation and mortality or body mass index, suggesting social isolation may be equally harmful for men and women (Holt-Lunstad et al. 2010; Kobayashi and Steptoe 2018). Still, other research has found that social isolation is associated with worse health, including hypertension and larger waist circumference, in women but not men (Hosseini et al. 2020, 2021). This could be because men receive a majority of their needed social support from their spouses/partners, while women rely on their broader networks for support (Röhr et al. 2021; Vandervoort 2000). Thus, social isolation may be more strongly associated with the health of women than men because socially isolated women lack the broader networks from which women receive most of their support. Further, literature on the effects of health on social isolation has found that hearing loss was related to higher levels of social isolation for women than for men (Mick et al. 2014). These previous findings lead me to hypothesize that:

Hypothesis 4: There will be gender differences in the relationship between social isolation and self-rated health, with women having stronger associations between social isolation and self-rated health than men.

No current literature has examined gender disparities in the longitudinal relationship between social isolation and health across adulthood. Additionally, literature has not investigated gender differences in the reciprocal relationship between social isolation and health. This can help establish temporal ordering and determine whether social isolation confers a greater health risk for some population groups than others.

HYPOTHESIZED MODEL CONNECTING SOCIAL ISOLATION AND SELF-RATED HEALTH

Figure 3.1 shows a proposed longitudinal model linking social isolation and self-rated health. There are three key components to this model: social isolation, self-rated health, and their associations with each other. In this model, there is an autoregressive effect of social isolation, whereby isolation at one age is dependent on isolation at the previous age. Social isolation is also defined by a time-invariant intercept that captures enduring aspects of social isolation as individuals age. This conceptualization of social isolation was determined based on analyses in the previous empirical chapter. This model proposes both an autoregressive and growth process of self-rated health, which will be tested in this chapter. Lastly, in this model social isolation and self-rated health are linked together. Social isolation and self-rated health are correlated within each age grouping (double headed arrows labeled a). There are cross-lagged effects of social isolation and self-rated health which signify that social isolation at one age is predictive of self-rated health at the next age, and vice versa (single-headed arrows b and c). Additionally, the intercepts and slopes of social isolation and self-rated health are correlated (the bar, d).

DATA AND METHODS

Study Samples

To examine the relationship between social isolation and self-rated health across adulthood, I use the National Survey of Midlife Development in the United States (MIDUS; Waves I-III), and the Health and Retirement Study (HRS; 2006-2016; see the Data Section from Chapter One for more detail on these datasets). As with the previous empirical chapter, I restrict the MIDUS analysis to respondents from the national random digit dial sample and pool data in the HRS to create full samples. My analytic sample is the same as the previous empirical chapter. It includes respondents with valid control measures (race/ethnicity and educational attainment) and excludes respondents born before 1915 and those born after 1954 in the HRS due to small sample sizes and limited follow-up periods to match the previous analysis. Missing data is again addressed through full information maximum likelihood (Arbuckle 1996).

Measures

My main variables of interest are social isolation and self-rated health. Social isolation is measured in accordance with the social isolation measures created in the first empirical chapter, a sum of four types of social relationships: relationship status, frequency of contact with friends and family, religious group attendance, and community involvement. This results in an index ranging from zero to four, with higher scores indicating more isolation (see the Measures Section from Chapter One for more detail). As for self-rated health, the measure was assessed in MIDUS by asking “In general, would you say your physical health is excellent, very good, good, fair, or poor?” Likewise, HRS assessed self-rated health by asking “Would you say your health is excellent, very good, good, fair, or poor?”. Higher values of the self-rated health measure indicate poorer health. Therefore, I refer to this measure throughout the analyses as poor self-rated health. Gender was assessed with a dummy variable (0 = men, 1 = women). Covariates include educational attainment (less than high school, high school degree [reference], some college, college degree or higher) and race/ethnicity (non-Hispanic White [reference], non-Hispanic Black, Hispanic, and non-Hispanic Other Races)[4].

Analytic Approach

The analyses occurred in three steps. First, I tested various longitudinal models of self-rated health in MIDUS and HRS, which are an extension of research conducted by Bollen and Gutin (2021) to examine longitudinal models of self-rated health in the National Longitudinal Study of Adolescent to Adult Health (Add Health) and the National Longitudinal Survey of Youth 1997 (NLSY97). To determine the best fitting longitudinal model of self-rated health in MIDUS and HRS, I replicated the longitudinal models used by Bollen and Gutin (2021), which are also the same longitudinal models I tested in empirical Chapter Two for social isolation (enduring, spontaneous, lagged effects, life course, and hybrid). The equations for these models are the same as in empirical Chapter Two; in the current chapter, Y_{it} becomes self-rated health instead of social isolation (refer to the Analytic Approach Section in empirical Chapter Two).

Second, I ran models testing the relationship between social isolation and self-rated health separately in MIDUS and HRS. In these two datasets I used the best fitting trajectory model of social isolation, the Autoregressive Latent Trajectory Intercept Only Model, which was assessed in the previous empirical chapter, and the longitudinal model of self-rated health, which was determined in the first stage of this analysis. In each dataset I ran stepwise models adding parameters to determine the relationship between social isolation and self-rated health. Again,

[4] I did not examine cohort differences in the relationship between social isolation and self-rated health because there is no theoretical or empirical evidence that would suggest that social isolation affects self-rated health differently by birth cohort.

my conceptual model (Figure 3.1) displays these hypothesized paths. First, I added correlations between the intercepts and slopes of social isolation and self-rated health (bar “h” in Figure 3.1). Second, I tested for correlations between social isolation and self-rated health within each age grouping (“a” in Figure 3.1). Third, I added cross-lagged effects, starting first with poor self-rated health being regressed on social isolation (“b” in Figure 3.1) and then adding the regressions of social isolation on poor self-rated health (“c” in Figure 3.1). I then tested a series of equality constraints, testing whether any of the added correlations or regressions were equal across age groupings. All models controlled for race/ethnicity and educational attainment.

Third, I examined whether the longitudinal association between social isolation and self-rated health varied by gender by testing for model invariance between women and men. To test for invariance, I took the best fitting model of the longitudinal relationship between social isolation and poor self-rated health found in the previous step of this analysis and fit a series of constrained nested models. Initially, I did not include any constraints except for model structure, which results in gender-stratified models. Next, I constrained the intercepts and slopes of social isolation and poor self-rated health to be equal for women and men. I then sequentially tested whether there are gender differences in the within-age correlations and the cross-lagged regressions of social isolation and self-rated health.

RESULTS

Descriptive Results

Tables 3.1A and 3.1B present weighted descriptive statistics of the social isolation index, poor self-rated health, gender, race/ethnicity, and educational attainment for MIDUS and HRS, respectively. The descriptive statistics for the social isolation index, gender, race/ethnicity, and educational attainment match the descriptives from the previous empirical chapter. Again, social isolation ranges from 0 to 4 with mean values ranging from 1.15 to 1.42 in MIDUS and 1.38 to 2.13 in HRS. The samples are majority white, have slightly more women than men, and most individuals have at least some college education. As for self-rated health, both datasets show that self-rated health worsens as individuals age.

Longitudinal Models of Self-Rated Health

To determine the trajectory of self-rated health within individuals as they age, I tested six longitudinal models: the Latent Time Invariant Model, Autoregressive Model (with and without autoregressive coefficients constrained to be equal across age groups), Linear Growth Curve Model, and the Autoregressive Latent Trajectory (ALT) Intercept Only Model (with and without the autoregressive coefficients constrained to be equal across age groups). The Spontaneous Model is not included because this model suggests that there is no systematic longitudinal pattern of social isolation and is assessed by examining R-squared values. Additionally, the ALT Growth Model did not converge in either dataset.

Fit statistics indicate that the Linear Growth Curve Model is the best fitting longitudinal model of self-rated health (SRH) in both MIDUS and HRS (Tables 3.2A and 3.2B). In MIDUS, the Linear Growth Model has a CFI and TLI close to 1: 0.974 and 0.958, respectively. Additionally, the RMSEA is close to 0 at 0.013, the Chi-Squared value is the lowest of all the models at 138, and the BIC is both negative and has the largest absolute magnitude at 571. Similarly, the Linear Growth Curve Model is the best fitting model across all fit statistics in the HRS (CFI = 0.979, TFI = 0.967, RMSEA = 0.012, Chi-Squared = 751, and BIC = -676).

Table 3.3A presents estimates from the Linear Growth Curve Model of SRH in MIDUS. The model shows that mean SRH at age 25 to 29 is 2.42, which corresponds to good/very good SRH, with SRH worsening as individuals age (coefficient(coef.) = 0.06; p = <0.001). While there is significant variation in mean levels of SRH across individuals (p = <0.001) at the first age group (ages 25-29), there is little variation in rates of change of SRH across people (p = 0.131). The R-squared values, which specify how much of the variation in poor SRH is explained by the model, gradually increases with age, from 0.44 at ages 25-29 to 0.62 at ages 80 and older.

Results from the Growth Curve Model in HRS (Table 3.3B) exhibit similar findings as the MIDUS results, with a few differences. Mean SRH at the intercept, ages 50-52, is 2.65 (p = <0.001) which is slightly higher than in MIDUS. This is expected given the HRS sample is older. Poor SRH similarly worsens with age in HRS (coef. = 0.04; p = <0.001). While there is not a significant relationship between mean levels of SRH at the first age group (ages 50-52) and rates of change of SRH in MIDUS, the HRS results indicate that poorer SRH at the intercept is related to less steep declines in SRH with age (coef. = -0.02; p = <0.001). This is likely due to a ceiling effect, where those in poor health cannot rate their health any lower. However, as individuals age, more people may move from good to poor health (Jackson and Engelman 2021). Results also show significant differences in mean levels of SRH at the first age group (ages 50-52) and in rates of change of SRH across people in HRS (p = <0.001). Lastly, the R-squared values decline slightly with advancing age, from 0.69 at ages 50-52 to 0.63 at ages 89 and older. This indicates that around 65 percent of the variation in poor SRH is explained by the model, which includes a latent intercept, slope, variances, covariates (race/ethnicity and education), and a correlation between the intercept and slope.

Reciprocal Relationship Between Social Isolation and Self-Rated Health

To examine the relationship between social isolation and poor self-rated health (SRH), I took the best fitting longitudinal model of each (Growth Curve Model for SRH and the ALT Intercept Only Model for social isolation) and added correlations between the latent intercepts and slope, correlations between social isolation and SRH within the same age group, and cross-lagged regressions. These paths were added in a stepwise fashion. I then tested equality constraints by age for each of these paths. For MIDUS, I found that a model which only includes correlations between the intercepts and slope of social isolation and poor SRH was the best fitting model (Model A; Table 3.4A). This model has the lowest BIC at -2263, a CFI and TLI close to 1 at 0.983 and 0.978, and a RMSEA of 0.007. These model fit statistics in combination with insignificant within-age correlations and cross-lagged regressions provides support for Model A.

Table 3.5A presents parameter estimates for Model A (with significant paths visually represented in Figure 3.2A) in MIDUS. Of particular interest are the correlations between poor SRH and social isolation and the R-squared values, as the other parameter estimates mirror results of the best fitting models of SRH and social isolation from the previous section and previous empirical chapter, respectively. Results indicate that the latent intercepts of social isolation and poor SRH are positively correlated (coef. = 0.06; p = <0.001). These results suggest that time-invariant factors which influence social isolation are related to initial values of poor SRH. Therefore, similar factors which impact social isolation also impact poor SRH. Overall, results show little significant relationships between social isolation and poor SRH, which I examine further in the discussion section.

Meanwhile in HRS, Model F, which includes all paths between social isolation and poor SRH as well as equality constraints for the within-age group correlations and the regression of poor SRH on social isolation, is the best fitting model (Table 3.4B). Model F has the lowest BIC at -3227, one of the highest TLI values at 0.979, and one of the lowest RMSEA values at 0.008. While Models D (with no equality constraints) and E (only with equality constraints for the within age group correlations) have similar CFI, TLI, and RMSEA values, the BIC values as well as the significant Chi-Squared tests indicate that Model F is the best fitting model.

Estimates for the bivariate relationship between social isolation and poor SRH in HRS, Model F, are displayed in Table 3.5B (with significant paths visually represented in Figure 3.2B). Similar to MIDUS, the latent intercepts of social isolation and poor SRH are positively correlated in HRS (coef. = 0.17; p = <0.001). Additionally, in HRS, the time-invariant factors influencing social isolation are associated with slower declines in SRH. Results from the cross-lagged regressions suggest that there is a reciprocal relationship between social isolation and poor SRH, meaning that not only does social isolation influence poor SRH, but also that poor SRH influences social isolation. Specifically, this model indicates that increasing levels of social isolation at one age is related to worsening SRH at the next age (coef. = 0.04; p = <0.001), with the magnitude of this relationship remaining consistent across late mid-to-late adulthood. While worsening SRH is associated with higher levels of social isolation from one time to the next, this relationship is only significant at older ages. This suggests that poor SRH may not have an impact on social isolation until later in life, around ages 75 and older. Additionally, as individuals age, changes in poor SRH are more strongly related to changes in social isolation. For example, at ages 80 to 82, a one-unit increase in poor SRH is related to a 0.08-unit (p = <0.001) increase in social isolation at ages 83 to 85. Meanwhile, a one-unit increase in poor SRH at ages 86 to 88 is related to a 0.25-unit (p = <0.001) increase in social isolation at ages 89 and older. Social isolation and poor SRH are also positively related to each other within each age group (coef. = 0.03; p = <0.001).

Gender Differences in the Relationship Between Social Isolation and Self-Rated Health

Next, I examined gender differences in the relationship between social isolation and poor self-rated health. In MIDUS, I tested for model invariance using the best fitting bivariate model that included all the paths between social isolation and poor SRH. While a model which only included correlations between the intercepts and slope was the best fitting model overall, there may be gender differences in the within-age group correlations between social isolation and poor SRH or cross-lagged regressions, which may not be discernable in the overall findings. Therefore, I tested for gender differences in the next best fitting model in MIDUS, which was a model that included correlations between the intercepts and slope of social isolation and poor SRH as well as included within-age group correlations and cross-lagged regressions that were constrained to be equal across all age groups (CFI = 0.983, TFI = 0.977, RMSEA = 0.007, Chi-Squared = 391, and BIC = -2241; Table 3.4A). The best fitting gender model was Model E, which constrained correlations between the latent intercepts and slope, within-age correlations, and cross-lagged regressions to be equal by gender (Table 3.6A). The model has a CFI and TLI close to 1: 0.969 and 0.958, RMSEA close to 0 at 0.010, and a negative BIC that is high in absolute value at 4519. Overall, results indicate that there are no significant gender differences in the relationship between social isolation and poor SRH in MIDUS. This finding is further supported in Table 3.7A, which displays the unconstrained parameters of the relationship between social isolation and poor SRH by gender. It shows largely insignificant differences between the parameter estimates for men and women.

For HRS, I used Model E from the previous steps' bivariate models to examine gender differences, which included all paths as well as equality constraints for correlations of social isolation and poor SRH within age groupings (Table 3.4B). While Model F, which additionally included equality constraints by age for the regressions of poor SRH on social isolation, was the best fitting bivariate model, none of the model invariant tests using Model F converged. Therefore, I used the second-best fitting bivariate model, Model E (Table 3.4B), which allowed the regression of poor SRH on social isolation to differ by age, for the model invariance tests. Fit statistics for the invariance models suggest that Model E (Table 3.6B), in which all paths between social isolation and poor SRH are constrained to be equal for men and women, may be the best fitting model (CFI = 0.983, TFI = 0.977, RMSEA = 0.008, Chi-Squared = 2083, and BIC = -7027). However, there are only slight differences in the fit statistics across models, making it difficult to definitively determine the best fitting model by gender. I further investigated gender differences by examining the unconstrained parameters in the bivariate models of social isolation and poor SRH for men and women (Table 3.7B). Parameter estimates indicate no gender differences in the correlations between the intercepts and slope, within age group correlations, or in the regression of social isolation on poor SRH. However, results suggest that there may be gender differences in the cross-lagged regression of poor SRH on social isolation, as increases in social isolation are only associated with worsening health for women. This is denoted through the largely significant regressions of poor SRH on social isolation for women, but no significant relationships for men. However, these results should be interpreted with caution given that a model which indicates no gender differences in social isolation and poor SRH fits the data slightly better than a model which includes gender differences in the regression of poor SRH on social isolation.

DISCUSSION

Social isolation is a public health issue that has worsened during the COVID-19 pandemic. While literature has documented the damaging effects of social isolation, there are still gaps in our knowledge, including in the age groups examined, the reciprocal relationship between social isolation and health, and the differential health consequences by gender. As the U.S. moves to a new phase of the pandemic, it is important to address these gaps as new policies and programs are developed as a result of the pandemic. This chapter used two nationally representative longitudinal datasets comprising of adults aged 25 to 101 to examine how trajectories of social isolation are related to trajectories of self-rated health and how this association varies by gender. I highlight findings related to the three key areas described above.

First, the relationship between social isolation and self-rated health changes with age. This chapter extends previous literature by determining the trajectory of both social isolation and self-rated health, instead of just one or the other. This allowed me to examine how changes in social isolation are related to changes in self-rated health, and vice versa. In determining the longitudinal structure of self-rated health, I found that a Growth Curve Model best fit the data, suggesting that self-rated health worsens with age, in-line with previous literature (McCullough and Laurenceau 2004; Sargent-Cox et al. 2010; Sokol et al. 2017). While social isolation and self-rated health are not closely related in young adulthood and midlife, they are in older adulthood. This supports my hypothesis that the magnitude of the association between social isolation and self-rated health is stronger at older ages than younger ages. Social isolation may be particularly detrimental for older adults because, as health begins to decline with advancing age, socially isolated older adults have few social connections to provide support and resources, which can further accelerate declining health.

Yet, unlike previous literature, I did not find that social isolation was associated with poorer self-rated health at all ages (Hämmig 2019). The few within-person linkages between social isolation and self-rated health in young adulthood and midlife could be due to several substantive explanations. During midlife, adults are embedded in multiple social contexts including those with their children, aging parents, and the community (Lachman 2004; Yang et al. 2016). These extensive connections during midlife may result in little changes in levels of isolation during this stage of the life course. Additionally, these relationships, such as caring for aging parents, may be stressful in nature and outweigh any positive benefits of the connections (Brim et al. 2004; Lachman 2004). In fact, research has found that during midlife the quality of social relationships may be more important than the quantity of social relationships (Carmichael et al. 2015; Yang et al. 2016).

Further, there may be methodological differences that are leading to few significant relationships between social isolation and self-rated health in MIDUS. Self-rated health was assessed in slightly different ways in MIDUS and HRS. In MIDUS, respondents were asked to rate their “physical health”, while HRS respondents were asked to rate their “health”. Although measures were assessed consistently within study, these measurement differences may have created different findings across studies. Particularly, respondents in the HRS may have used more psychosocial aspects to evaluate their health than MIDUS respondents, who were specifically asked about their physical health. However, research has found that older adults are more likely to take into account physical health factors when assessing their health; therefore the self-rated health in HRS may largely be capturing physical health (Jylhä 2009; Kaplan and Baron-Epel 2003). Additionally, although MIDUS has a large sample size, the combination of splitting the data by age group and the complexity of the models may have reduced power to determine statistical differences. This may be particularly true in the youngest and oldest age groups of MIDUS, where the data is the thinnest. Overall, more research is needed to better understand the relationship between social isolation and health in midlife.

Second, I find that there is a reciprocal relationship between social isolation and self-rated health, thus supporting my hypothesis and aligning with previous research (Ha et al. 2019; Kobayashi and Steptoe 2018; Sluzki 2010). Increases in isolation are related to worsening self-rated health in older adults, with this relationship remaining consistent across adults aged 50 and older. This analysis extends previous literature on the relationship between social isolation and self-rated health by examining longitudinal change over a multi-year period to establish temporal ordering. Changes in self-rated health can be found even three years after changes in isolation. Even though the changes are small, any significant within-person changes over this long of a period, after controlling for the effect of self-rated health on social isolation, helps demonstrate temporal ordering. This suggests that for older adults, changes in isolation can potentially have a lasting impact on self-rated health. Given that this relationship remains consistent across older adulthood, this indicates that any changes in isolation during the latter stage of the life course can be detrimental to self-rated health.

In addition to changes in isolation being related to changes in self-rated health, worsening self-rated health is related to higher levels of isolation. However, this relationship is only significant in late life. This could be because as physical and mental health declines, network members may provide social support, which can lead to the maintenance of social ties. It may not be until late life that health conditions dramatically increase, leading to limitations which can decrease social interaction. This may suggest that declining health does not lead to increasing isolation until health declines considerably in old age.

Third, I find few gender differences in the relationship between social isolation and self-rated health. The one exception is that women may experience greater health risks to being socially isolated than men in older adulthood. This partially supports my hypothesis that women will have stronger associations between social isolation and self-rated health than men. In young adulthood and midlife, there is again no relationship between social isolation and self-rated health for either women or men. In older adulthood, both men and women do not experience higher levels of isolation with worsening health until late life. This suggests that poor perceived health impacts social isolation in men and women equally.

However, in older adulthood, increases in social isolation may be associated with worsening self-rated health for women, but not men. This could be because women tend to rely on broad networks for social support and stress-buffering, while men often receive support from a smaller network (Röhr et al. 2021; Vandervoort 2000). Additionally, women face social expectations to maintain interpersonal relationships, particularly with family (Erickson 2005; McPherson et al. 2006; Umberson et al. 1996). Not meeting these societal norms may lead to women rating their health more poorly. Women may particularly experience a greater health risk to social isolation in older adulthood as they experience widowhood at higher rates, and thus greater changes in their social network, than men (Mayol-García et al. 2021). However, more research is needed in this area.

Implications

This chapter provides insights for future research and policy. Social isolation can lead to worsening health in older adults, with the potential for lasting impacts. Therefore, policies and programs are needed to address social isolation in this population, particularly as the U.S. population ages. This can include screening for social isolation at Medicare visits, partnerships between health care and social service providers, and connecting older adults to community-based services (National Academies of Sciences, Engineering, and Medicine 2020; Sonderlund, Thilsing, and Sondergaard 2019). Additionally, worsening self-rated health can lead to increases in isolation. This implies the need to examine the reciprocal relationship between measures of social isolation and health to better establish temporal ordering. In particular, I found that worsening self-rated health does not lead to increases in isolation until late life. Social support in the presence of declining health could offset potential increases in isolation, but more research is needed on potential mechanisms. Still, these findings suggest the need to develop solutions for those with declining health, particularly in late life, to maintain social connections. This can include addressing underlying issues such as hearing loss, accessibility to key resources, and knowledge of different communication technologies (National Academies of Sciences, Engineering, and Medicine 2020).

While I find few linkages between social isolation and self-rated health in young adulthood and midlife, more research is needed during these life stages as well as in earlier life stages to further explore this finding. For example, during adolescence and the transition to adulthood, there may be greater variation in levels of isolation, as these stages of the life course are marked by major life transitions (Hall-Lande et al. 2007; Harris 2010; Shanahan 2000). However, consistently measured longitudinal data on social isolation is limited at younger ages. Research is needed to determine how social isolation should be measured earlier in the life course and assessed over time. Additionally, more research is needed to determine if these findings are similar for different health outcomes.

Lastly, the relationship between social isolation and self-rated health is largely the same for men and women. However, women may experience more health risks to being socially isolated than men in older adulthood. Given that in older adulthood women experience widowhood at higher rates than men, interventions which target widowed women may be particularly beneficial. Some bereavement interventions for widowed adults have found some promising results (Chow et al. 2019; Stewart et al. 2001). Additionally, future research should examine whether there are gender differences in the relationship between social isolation and self-rated health when taking relationship status out of the social isolation index. Indeed, my previous empirical chapters showed differences in the prevalence of isolation based on whether or not relationship status was included or excluded in the measure.

Limitations

Several limitations should be acknowledged. First, as in the previous empirical chapter, models are unweighted because of the complexities of weighting with the model structure and the amount of missing data. To help account for this, I included control variables that were utilized to calculate the weights. Additionally, some models did not converge due to model complexity and missing data. However, evidence suggests that the models that did not converge would not have fit the data the best. Second, as mentioned previously, self-rated health was assessed in different ways in MIDUS and HRS, which may have created different findings across studies. Third, model fit statistics sometimes led to conflicting evidence to which model fit the data the best. I used both overall fit statistics and components of model fit to determine the best fitting models. However, further research conducted in other samples may find less ambiguity.

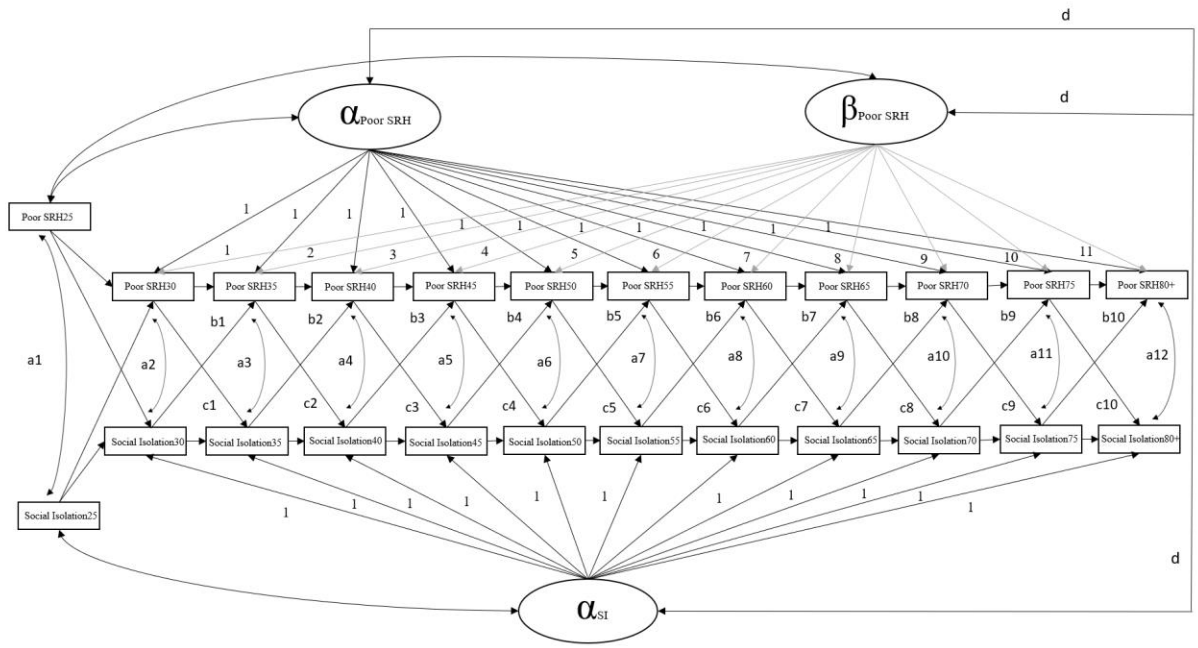
Lastly, I did not account for measurement error in self-rated health. Although previous research has found that self-rated health has moderate reliability, about 0.60, models accounting for this error would either not converge or produced implausible values such as negative error variances (Bollen and Gutin 2021; Zajacova and Dowd 2011). This is likely due to the complexity of the models that make the models sensitive to additional specifications. Additionally, self-rated health only has a single indicator, which single-indicator models on their own can be difficult to estimate (Hoyle 2011). I tried multiple strategies including constraining error variances of the observed variables, latent variables, covariates, and combinations of these strategies, and still had issues getting these models to run. Models that did run, however, showed similar results to the final models I reported in this chapter below.

Conclusion

This chapter used two longitudinal nationally representative datasets to examine how social isolation and self-rated health are related across adulthood and how this association varies by gender. This study builds on previous literature by examining a wider age range of respondents, investigating the reciprocal relationship between social isolation and self-rated health, assessing both concepts longitudinally, and exploring gender differences in this longitudinal relationship. I find that the relationship between social isolation and self-rated health may be greater in older adulthood than in young adulthood and midlife. In particular, there is a reciprocal relationship between social isolation and self-rated health in older adults. Increases in social isolation were associated with worsening health in older adults; this remained consistent at ages 50 and older. Meanwhile, changes in self-rated health may only be related to changes in social isolation in late life. Additionally, there are few gender differences in the relationship between social isolation and self-rated health across adulthood, except that women in older adulthood may experience greater health risks to being socially isolated than men. These findings underscore the importance of addressing social isolation in older adulthood to prevent further declines in health.

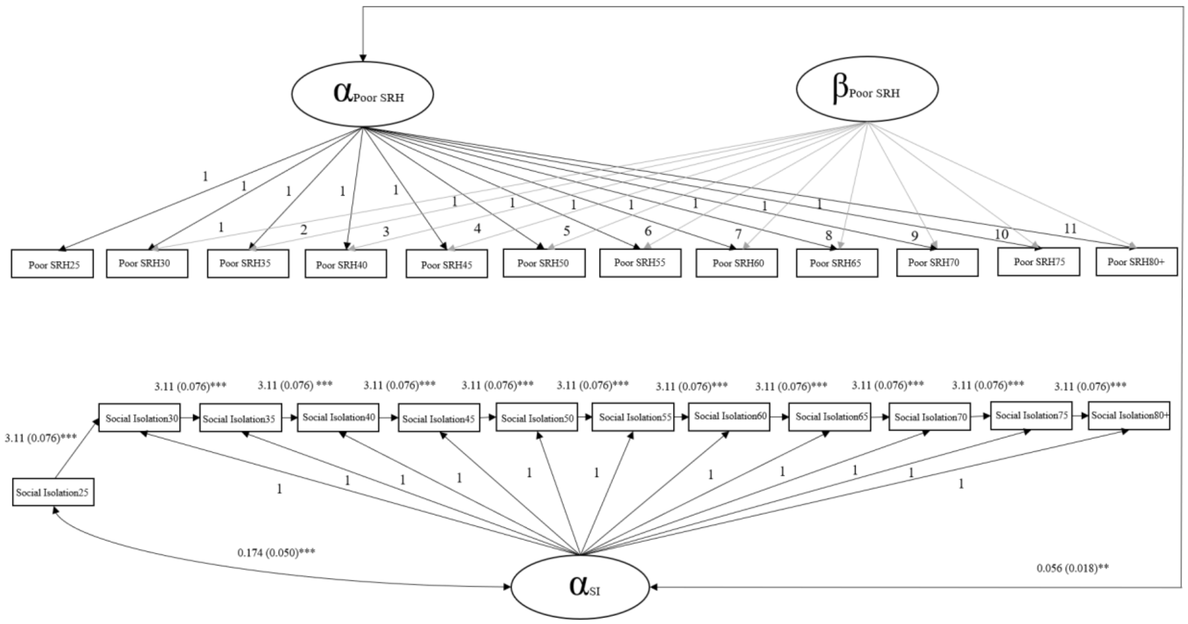
TABLES AND FIGURES

Figure 3.1. Hypothesized model connecting social isolation and self-rated health.



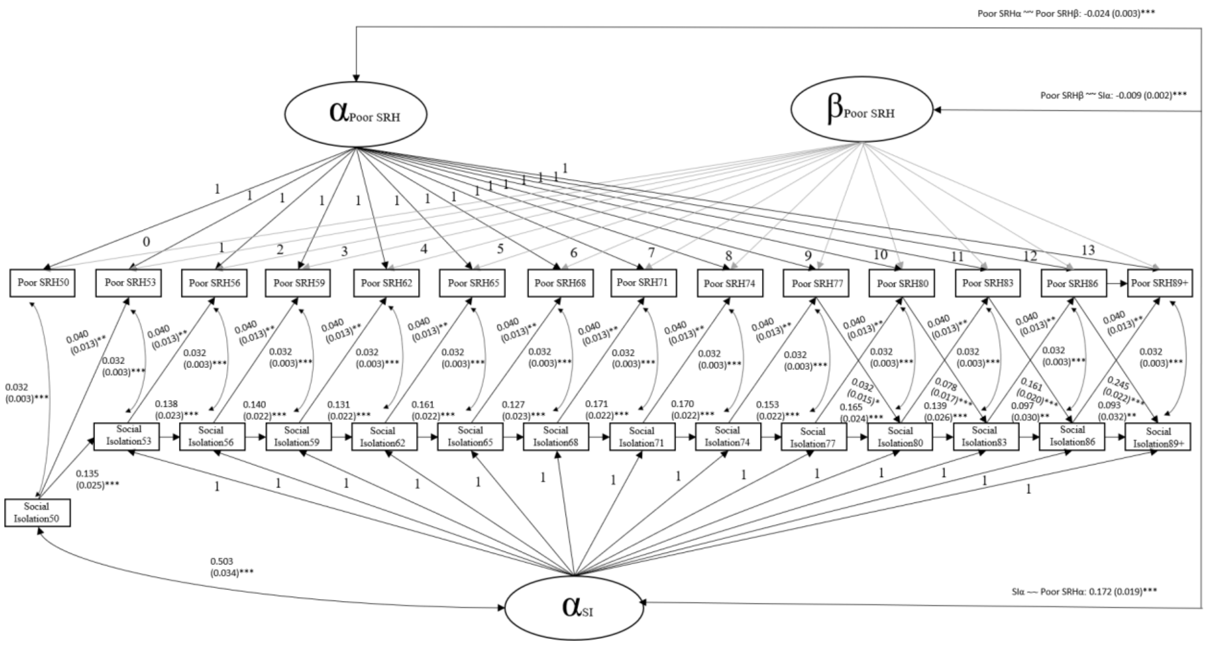
Note: Race/ethnicity and education are controlled for in all measures.; α = latent intercept, β = latent slope, SRH = self-rated health, SI = social isolation.

Figure 3.2A. Estimates from the bivariate model of social isolation and poor self-rated health, National Survey of Midlife Development in the United States, 1995-2014 (N = 3,052), Table 3.5A.



Note: Coefficients with standard errors in parenthesis are presented. Race/ethnicity and education are controlled for in all measures. Non-significant paths were omitted. BIC = -2263.65; CFI = 0.983; TLI = 0.978; RMSEA = 0.007. α = latent intercept, β = latent slope, SRH = self-rated health, SI = social isolation. *** p<0.001, ** p<0.01, * p<0.05.

Figure 3.2B. Estimates from the bivariate model of social isolation and poor self-rated health, Health and Retirement Study, 2006-2016 (N = 24,501), Table 3.5B.



Note: Race/ethnicity and education are controlled for in all measures. Non-significant paths were omitted. BIC = -3227.29; CFI = 0.985; TLI = 0.979; RMSEA = 0.008. α = latent intercept, β = latent slope, SRH = self-rated health, SI = social isolation

Table 3.1A. Weighted sample characteristics, National Survey of Midlife Development in the United States, 1995-2014 (N = 3,052)

Variables	Mean(SD) / Proportion
Social isolation index (0-4)	
25-29	1.42 (0.90)
30-34	1.24 (0.90)
35-39	1.19 (0.98)
40-44	1.17 (0.96)
45-49	1.24 (0.97)
50-54	1.27 (0.99)
55-59	1.22 (0.96)
60-64	1.22 (0.96)
65-69	1.20 (0.95)
70-74	1.19 (0.96)
75-79	1.15 (0.96)
80+	1.40 (1.02)
Poor self-rated health (1-5)	
25-29	2.41 (0.93)
30-34	2.41 (0.90)
35-39	2.36 (0.90)
40-44	2.48 (1.02)
45-49	2.50 (0.98)
50-54	2.60 (0.99)
55-59	2.56 (1.09)
60-64	2.68 (1.07)
65-69	2.77 (1.01)
70-74	2.84 (1.12)
75-79	2.96 (1.05)
80+	2.86 (1.05)
Women	0.53
Race/ethnicity	
Non-Hispanic White	0.81
Non-Hispanic Black	0.08
Hispanic	0.07
Non-Hispanic Other Races	0.04
Educational attainment	
Less than high school degree	0.11
High school degree	0.33
Some college	0.28
College degree or higher	0.28

Table 3.1B. Weighted sample characteristics, Health and Retirement Study, 2006-2016 (N = 24,501)

Variables	Mean(SD) / Proportion
Social isolation index (0-4)	
50-52	1.39 (0.98)
53-55	1.38 (1.02)
56-58	1.42 (1.03)
59-61	1.43 (1.04)
62-64	1.45 (1.03)
65-67	1.42 (1.05)
68-70	1.40 (1.03)
71-73	1.39 (1.06)
74-76	1.42 (1.07)
77-79	1.46 (1.05)
80-82	1.59 (1.08)
83-85	1.67 (1.05)
86-88	1.86 (1.05)
89+	2.13 (1.00)
Poor self-rated health (1-5)	
50-52	2.61 (1.08)
53-55	2.68 (1.11)
56-58	2.74 (1.11)
59-61	2.75 (1.10)
62-64	2.79 (1.07)
65-67	2.77 (1.07)
68-70	2.81 (1.05)
71-73	2.86 (1.05)
74-76	2.93 (1.07)
77-79	3.01 (1.08)
80-82	3.05 (1.05)
83-85	3.07 (1.09)
86-88	3.09 (1.06)
89+	3.16 (1.02)
Women	0.53
Race/ethnicity	
Non-Hispanic White	0.75
Non-Hispanic Black	0.11
Hispanic	0.10
Non-Hispanic Other Races	0.04
Educational attainment	
Less than high school degree	0.17
High school degree	0.30

Some college	0.25
College degree or higher	0.28

Table 3.2A. Comparison of fit statistics for trajectories of poor self-rated health, the National Survey of Midlife Development in the United States, 1995-2014 (N = 3,052)

Model	x^2	DF	BIC	CFI	TLI	RMSEA
Latent Time-Invariant	224.65	87	-527.08	0.933	0.894	0.020
Autoregressive (AR Constrained)	395.41	75	-351.74	0.870	0.761	0.030
Autoregressive	381.66	65	-297.31	0.881	0.747	0.031
Linear Growth Curve	138.11	84	-571.25	0.974	0.958	0.013
ALT Intercept Only (AR Constrained)	266.73	89	-523.87	0.919	0.874	0.022
ALT Intercept Only	174.19	79	-519.45	0.960	0.930	0.016

Notes: Full informational maximum likelihood was used to account for missing data. Models were run with robust maximum likelihood, controlled for race and education, and self-rated health variances were constrained to equal by age. ALT Growth Model did not converge. AR = autoregressive equation, ALT = autoregressive latent trajectory.

Table 3.2B. Comparison of fit statistics for trajectories of poor self-rated health, the Health and Retirement Study, 2006-2016 (N = 24,501)

Model	x^2	DF	BIC	CFI	TLI	RMSEA
Latent Time-Invariant	1120.34	116	-469.45	0.967	0.949	0.015
Autoregressive (AR Constrained)	3642.47	103	934.12	0.898	0.827	0.028
Autoregressive	3902.05	91	865.64	0.907	0.822	0.028
Linear Growth Curve	751.39	113	-676.02	0.979	0.967	0.012
ALT Intercept Only (AR Constrained)	1271.18	118	-394.54	0.962	0.943	0.016
ALT Intercept Only	1185.86	106	-387.10	0.967	0.945	0.015

Notes: Full informational maximum likelihood was used to account for missing data. Models were run with robust maximum likelihood, controlled for race and education, and self-rated health variances were constrained to equal by age. ALT Growth Model did not converge. AR = autoregressive equation, ALT = autoregressive latent trajectory.

Table 3.3A. Select parameter estimates from the Linear Growth Curve Model, National Survey of Midlife Development in the United States, 1995-2014 (N = 3,052)

Parameter	Estimate	Std. Err.	P-value
Intercept			
Intercept	2.423	0.056	<0.001
Slope	0.058	0.010	<0.001
Covariances			
Intercept ~~ Slope	0.004	0.009	0.672
Variances			
Poor SRH_t (constrained to equal across $_t$)	0.476	0.015	<0.001
Intercept	0.338	0.048	<0.001
Slope	0.003	0.002	0.131
R-square			
Poor SRH 80	0.622		
Poor SRH 75	0.627		
Poor SRH 70	0.608		
Poor SRH 65	0.581		
Poor SRH 60	0.566		
Poor SRH 55	0.547		
Poor SRH 50	0.516		
Poor SRH 45	0.510		
Poor SRH 40	0.500		
Poor SRH 35	0.473		
Poor SRH 30	0.462		
Poor SRH 25	0.444		

Notes: Full informational maximum likelihood was used to account for missing data. Models were run with robust maximum likelihood and controlled for race and educational attainment.
x^2 = 138; DF = 84; BIC = -571.25; CFI = 0.974; TLI = 0.958; RMSEA = 0.013
SRH = self-rated health; t = 25-29; 30-34, 35-39, 40-44, 45-49, 50-54, 55-59, 60-64, 65-69, 70-74, 75-79, 80+

Table 3.3B. Select parameter estimates from the Linear Growth Curve Model, Health and Retirement Study, 2006-2016 (N = 24,501)

Parameter	Estimate	Std. Err.	P-value
Intercept			
Intercept	2.651	0.022	<0.001
Slope	0.042	0.003	<0.001
Covariances			
Intercept ~~ Slope	-0.020	0.004	<0.001
Variances			
Poor SRHt (constrained to equal across $_t$)	0.422	0.005	<0.001
Intercept	0.758	0.022	<0.001
Slope	0.003	0.001	<0.001
R-square			
Poor SRH 89	0.625		
Poor SRH 86	0.627		
Poor SRH 83	0.619		
Poor SRH 80	0.622		
Poor SRH 77	0.625		
Poor SRH 74	0.621		
Poor SRH 71	0.623		
Poor SRH 68	0.628		
Poor SRH 65	0.640		
Poor SRH 62	0.651		
Poor SRH 59	0.661		
Poor SRH 56	0.669		
Poor SRH 53	0.677		
Poor SRH 50	0.690		

Notes: Full informational maximum likelihood was used to account for missing data. Models were run with robust maximum likelihood and controlled for race and educational attainment.
x^2 = 751; DF = 113; BIC = -676.02; CFI = 0.979; TLI = 0.967; RMSEA = 0.012
SRH = self-rated health; t = 50-52, 53-55, 56-58, 59-61, 62-64, 65-67, 68-70, 71-73, 74-76, 77-79, 80-82, 83-85, 86-88, 89+

Table 3.4A. Comparison of fit statistics for bivariate models of social isolation and poor self-rated health, the National Survey of Midlife Development in the United States, 1995-2014 (N = 3,052)

Model	x^2	DF	BIC	CFI	TLI	RMSEA	Model Comparison	x^2 Difference Test
Adding Parameters								
A: Correlations between the intercepts and slope of SI and Poor SRH	390.46	315	-2263.65	0.983	0.978	0.007	B vs. A	0.551
B: Model A + Within age correlations between SI and Poor SRH	382.00	303	-2178.42	0.983	0.976	0.008	C vs. B	0.518
C: Model B + Cross-lagged regressions of SI -> Poor SRH	375.24	292	-2102.54	0.983	0.975	0.008	D vs. C	0.175
D: Model C + Cross-lagged regressions of Poor SRH -> SI	359.14	281	-2032.03	0.984	0.976	0.008		
Adding Constraints								
E: Model D + Equality constraints for within age correlations of SI and Poor SRH by age	370.68	292	-2106.82	0.984	0.976	0.007	D vs. E	0.323
F: Model E + Equality constraints on SI -> Poor SRH regressions by age	372.56	302	-2177.72	0.985	0.979	0.007	E vs. F	0.707
G: Model F + Equality constraints on Poor SRH -> SI regressions by age	391.03	312	-2240.78	0.983	0.977	0.007	F vs. G	0.093

Notes: Full informational maximum likelihood was used to account for missing data. Models were run with robust maximum likelihood, controlled for race and education, and social isolation and self-rated health variances were constrained to equal by age.

SI = social isolation; SRH = self-rated health

Table 3.4B. Comparison of fit statistics for bivariate models of social isolation and poor self-rated health, the Health and Retirement Study, 2006-2016 (N = 24,501)

Model	x^2	DF	BIC	CFI	TLI	RMSEA	Model Comparison	x^2 Difference Test
Adding Parameters								
A: Correlations between the intercepts and slope of SI and Poor SRH	2296.49	413	-2944.88	0.974	0.965	0.010	B vs. A	<0.001
B: Model A + Within age correlations between SI and Poor SRH	2081.44	399	-2959.21	0.977	0.969	0.009	C vs. B	<0.001
C: Model B + Cross-lagged regressions of SI -> Poor SRH	2084.77	386	-2871.77	0.978	0.969	0.009	D vs. C	<0.001
D: Model C + Cross-lagged regressions of Poor SRH -> SI	1533.80	373	-3042.15	0.986	0.979	0.008		
Adding Constraints								
E: Model D + Equality constraints for within age correlations of SI and Poor SRH by age	1545.86	386	-3134.68	0.985	0.979	0.008	D vs. E	<0.001
F: Model E + Equality constraints on SI -> Poor SRH regressions by age	1540.76	398	-3227.29	0.985	0.979	0.008	E vs. F	0.017
G: Model F + Equality constraints on Poor SRH -> SI regressions by age	2031.28	410	-3063.65	0.977	0.970	0.009	F vs. G	<0.001

Notes: Full informational maximum likelihood was used to account for missing data. Models were run with robust maximum likelihood, controlled for race and education, and social isolation and self-rated health variances were constrained to equal by age.

SI = social isolation; SRH = self-rated health

Table 3.5A. Select parameter estimates from the bivariate model of social isolation and poor self-rated health, National Survey of Midlife Development in the United States, 1995-2014 (N = 3,052)

Parameter	Estimate	Std. Err.	P-value
Autoregressives (with all coefficients equal)			
SI_t ~ SI_t-1	0.311	0.076	<0.001
Intercept			
SI Intercept	0.921	0.105	<0.001
Poor SRH Intercept	2.421	0.056	<0.001
Poor SRH Slope	0.058	0.010	<0.001
Mean			
SI 25	1.443	0.052	<0.001
Covariances			
SI Intercept ~~ SI 25	0.174	0.050	<0.001
SI Intercept ~~ Poor SRH Intercept	0.056	0.018	0.002
SI Intercept ~~ Poor SRH Slope	-0.002	0.003	0.500
Poor SRH Intercept ~~ Poor SRH Slope	0.003	0.009	0.698
Variances			
SI_t (constrained to equal across $_t$)	0.475	0.015	<0.001
SI 25	0.818	0.056	<0.001
Poor SRH_t (constrained to equal across $_t$)	0.377	0.013	<0.001
SI Intercept	0.233	0.059	<0.001
Poor SRH Intercept	0.339	0.048	<0.001
Poor SRH Slope	0.003	0.002	0.120
R-square			
SI 80	0.617		
SI 75	0.609		
SI 70	0.603		
SI 65	0.598		
SI 60	0.603		
SI 55	0.604		
SI 50	0.611		
SI 45	0.622		
SI 40	0.609		
SI 35	0.595		
SI 30	0.552		
Poor SRH 80	0.623		
Poor SRH 75	0.627		
Poor SRH 70	0.609		
Poor SRH 65	0.581		
Poor SRH 60	0.566		
Poor SRH 55	0.548		

Poor SRH 50	0.516
Poor SRH 45	0.510
Poor SRH 40	0.500
Poor SRH 35	0.473
Poor SRH 30	0.462
Poor SRH 25	0.445

Notes: Full informational maximum likelihood was used to account for missing data. Models were run with robust maximum likelihood and controlled for race and educational attainment.

x^2 = 391; DF = 315; BIC = -2263.65; CFI = 0.983; TLI = 0.978; RMSEA = 0.007

SI = social isolation; SRH = self-rated health; t = 30-34, 35-39, 40-44, 45-49, 50-54, 55-59, 60-64, 65-69, 70-74, 75-79, 80+

Table 3.5B. Select parameter estimates from the bivariate model of social isolation and poor self-rated health, Health and Retirement Study, 2006-2016 (N = 24,501)

Parameter	Estimate	Std. Err.	P-value
Autoregressives			
SI 89 ~ SI 86	0.093	0.032	0.004
SI 86 ~ SI 83	0.097	0.030	0.001
SI 83 ~ SI 80	0.139	0.026	<0.001
SI 80 ~ SI 77	0.165	0.024	<0.001
SI 77 ~ SI 74	0.153	0.022	<0.001
SI 74 ~ SI 71	0.170	0.022	<0.001
SI 71 ~ SI 68	0.171	0.022	<0.001
SI 68 ~ SI 65	0.127	0.023	<0.001
SI 65 ~ SI 62	0.161	0.022	<0.001
SI 62 ~ SI 59	0.131	0.022	<0.001
SI 59 ~ SI 56	0.140	0.022	<0.001
SI 56 ~ SI 53	0.138	0.023	<0.001
SI 53 ~ SI 50	0.135	0.025	<0.001
Cross-Lagged Regressions			
SI 89 ~ Poor SRH 86	0.245	0.022	<0.001
SI 86 ~ Poor SRH 83	0.161	0.020	<0.001
SI 83 ~ Poor SRH 80	0.078	0.017	<0.001
SI 80 ~ Poor SRH 77	0.032	0.015	0.033
SI 77 ~ Poor SRH 74	0.003	0.014	0.835
SI 74 ~ Poor SRH 71	-0.009	0.014	0.544
SI 71 ~ Poor SRH 68	-0.023	0.014	0.097
SI 68 ~ Poor SRH 65	-0.013	0.015	0.376
SI 65 ~ Poor SRH 62	-0.021	0.015	0.147
SI 62 ~ Poor SRH 59	-0.016	0.015	0.283
SI 59 ~ Poor SRH 56	-0.008	0.016	0.608
SI 56 ~ Poor SRH 53	-0.002	0.017	0.914
SI 53 ~ Poor SRH 50	-0.012	0.018	0.493
Poor SRH_t ~ SI_t-1 (constrained to equal across $_t$)	0.040	0.013	0.001
Intercept			
SI Intercept	1.290	0.047	<0.001
Poor SRH Intercept	2.584	0.027	<0.001
Poor SRH Slope	0.042	0.003	<0.001
Mean			
SI 50	1.389	0.028	<0.001
Covariances			
SI Intercept ~~ SI 50	0.503	0.034	<0.001
SI Intercept ~~ Poor SRH Intercept	0.172	0.019	<0.001

SI Intercept ~~ Poor SRH Slope	-0.009	0.002	<0.001
Poor SRH Intercept ~~ Poor SRH Slope	-0.024	0.003	<0.001
SI_t ~~ Poor SRH_t (constrained to equal across $_t$)	0.032	0.003	<0.001
Variances			
SI_t (constrained to equal across $_t$)	0.395	0.005	<0.001
SI 50	1.015	0.042	<0.001
Poor SRH_t (constrained to equal across $_t$)	0.421	0.005	<0.001
SI Intercept	0.470	0.026	<0.001
Poor SRH Intercept	0.771	0.022	<0.001
Poor SRH Slope	0.003	0.001	<0.001
R-square			
SI 89	0.651		
SI 86	0.639		
SI 83	0.650		
SI 80	0.655		
SI 77	0.646		
SI 74	0.652		
SI 71	0.645		
SI 68	0.624		
SI 65	0.637		
SI 62	0.625		
SI 59	0.629		
SI 56	0.631		
SI 53	0.622		
Poor SRH 89	0.632		
Poor SRH 86	0.630		
Poor SRH 83	0.620		
Poor SRH 80	0.622		
Poor SRH 77	0.624		
Poor SRH 74	0.619		
Poor SRH 71	0.621		
Poor SRH 68	0.627		
Poor SRH 65	0.639		
Poor SRH 62	0.652		
Poor SRH 59	0.663		
Poor SRH 56	0.672		
Poor SRH 53	0.679		
Poor SRH 50	0.695		

Notes: Full informational maximum likelihood was used to account for missing data. Models were run with robust maximum likelihood and controlled for race and educational attainment. x^2 = 1541; DF = 398; BIC = -3227.29; CFI = 0.985; TLI = 0.979; RMSEA = 0.008

SI = social isolation; SRH = self-rated health; t = 50-52, 53-55, 56-58, 59-61, 62-64, 65-67, 68-70, 71-73, 74-76, 77-79, 80-82, 83-85, 86-88, 89+

Table 3.6A. Model invariance by gender, the National Survey of Midlife Development in the United States, 1995-2014 (N = 3,052)

Model	x^2	DF	BIC	CFI	TLI	RMSEA	Model Comparison	x^2 Difference Test
A: No constraints except model structure	761.20	624	-4487.86	0.970	0.960	0.010		
B: Equality constraints for the intercepts and slope of SI and Poor SRH	771.31	626	-4495.86	0.968	0.957	0.010	B vs. A	0.030
C: Model B + Equality constraints of within age correlations of SI and Poor SRH	772.09	627	-4503.12	0.968	0.957	0.010	C vs. B	0.349
D: Model C + Equality constraints of SI -> Poor SRH regressions	771.60	628	-4511.11	0.968	0.958	0.010	D vs. C	0.863
E: Model D + Equality constraints of Poor SRH -> SI regressions	770.68	629	-4519.13	0.969	0.958	0.010	E vs. D	0.943

Notes: Full informational maximum likelihood was used to account for missing data. Models were run with robust maximum likelihood, controlled for race and education, and social isolation and self-rated health variances were constrained to equal by age.

SI = social isolation; SRH = self-rated health

Table 3.6B. Model invariance by gender, the Health and Retirement Study, 2006-2016 (N = 24,501)

Model	x^2	DF	BIC	CFI	TLI	RMSEA	Model Comparison	x^2 Difference Test
A: No constraints except model structure	2052.38	772	-6794.24	0.984	0.977	0.008		
B: Equality constraints for the intercepts and slope of SI and Poor SRH	2061.47	774	-6805.74	0.983	0.977	0.008	B vs. A	0.034
C: Model B + Equality constraints of within age correlations of SI and Poor SRH	2060.45	775	-6814.57	0.983	0.977	0.008	C vs. B	0.295
D: Model C + Equality constraints of SI -> Poor SRH regressions	2065.70	788	-6921.81	0.983	0.977	0.008	D vs. C	0.065
E: Model D + Equality constraints of Poor SRH -> SI regressions	2083.66	801	-7026.53	0.983	0.977	0.008	E vs. D	0.020
F: Model C + Equality constraints of Poor SRH -> SI regressions	2078.85	788	-6918.68	0.983	0.976	0.008	E vs. F	0.080

Notes: Full informational maximum likelihood was used to account for missing data. Models were run with robust maximum likelihood, controlled for race and education, and social isolation and self-rated health variances were constrained to equal by age.

Table 3.7A. Gender differences in unconstrained parameters of bivariate models of social isolation and poor self-rated health, National Survey of Midlife Development in the United States, 1995-2014 (N = 3,052)

	Men			Women		
Parameter	Estimate	Std. Err.	P-value	Estimate	Std. Err.	P-value
Autoregressives (with all coefficients equal)						
SI_t ~ SI_t-1	0.276	0.122	0.024	0.286	0.122	0.019
Cross-Lagged Regressions (constrained to equal across $_t$)						
SI_t ~ Poor SRH_t-1	0.064	0.093	0.490	-0.133	0.086	0.119
Poor SRH_t ~ SI_t-1	0.026	0.073	0.725	-0.152	0.077	0.048
Intercept						
SI Intercept	0.769	0.228	0.001	1.332	0.335	<0.001
Poor SRH Intercept	2.341	0.105	<0.001	2.671	0.135	<0.001
Poor SRH Slope	0.071	0.015	<0.001	0.047	0.014	0.001
Mean						
SI 25	1.548	0.074	<0.001	1.324	0.071	<0.001
Covariances						
SI Intercept ~~ SI 25	0.194	0.096	0.043	0.139	0.056	0.013
SI Intercept ~~ Poor SRH Intercept	-0.004	0.057	0.939	0.190	0.067	0.005
SI Intercept ~~ Poor SRH Slope	0.001	0.005	0.855	-0.001	0.005	0.796
Poor SRH Intercept ~~ Poor SRH Slope	0.010	0.012	0.380	0.005	0.013	0.700
SI_t ~~ Poor SRH_t (constrained to equal across $_t$)	-0.0001	0.013	0.975	0.002	0.012	0.884
Variances						
SI_t (constrained to equal across $_t$)	0.381	0.019	<0.001	0.357	0.017	<0.001
SI 25	0.843	0.073	<0.001	0.744	0.080	<0.001
Poor SRH_t (constrained to equal across $_t$)	0.477	0.022	<0.001	0.459	0.021	<0.001
SI Intercept	0.263	0.098	0.007	0.274	0.108	0.011
Poor SRH Intercept	0.256	0.060	<0.001	0.404	0.073	<0.001
Poor SRH Slope	0.002	0.002	0.431	0.002	0.002	0.441
R-square						
SI 80	0.653			0.636		
SI 75	0.630			0.628		

SI 70	0.617	0.613
SI 65	0.605	0.612
SI 60	0.608	0.612
SI 55	0.603	0.619
SI 50	0.607	0.628
SI 45	0.631	0.625
SI 40	0.604	0.643
SI 35	0.600	0.604
SI 30	0.582	0.551
Poor SRH 80	0.628	0.646
Poor SRH 75	0.632	0.639
Poor SRH 70	0.590	0.643
Poor SRH 65	0.565	0.611
Poor SRH 60	0.543	0.599
Poor SRH 55	0.552	0.565
Poor SRH 50	0.491	0.547
Poor SRH 45	0.479	0.546
Poor SRH 40	0.483	0.526
Poor SRH 35	0.452	0.495
Poor SRH 30	0.402	0.530
Poor SRH 25	0.399	0.501

Notes: Full informational maximum likelihood was used to account for missing data. Models were run with robust maximum likelihood and controlled for race and educational attainment. Based on Model A, no constraints except model structure.

x^2 = 761; DF = 624; BIC = -4487.86; CFI = 0.970; TLI = 0.960; RMSEA = 0.010

SI = social isolation; SRH = self-rated health; t = 25-29, 30-34, 35-39, 40-44, 45-49, 50-54, 55-59, 60-64, 65-69, 70-74, 75-79, 80+

Table 3.7B. Gender differences in unconstrained parameters of bivariate models of social isolation and poor self-rated health, Health and Retirement Study, 2006-2016 (N = 24,501)

	Men			Women		
Parameter	Estimate	Std. Err.	P-value	Estimate	Std. Err.	P-value
Autoregressives						
SI 89 ~ SI 86	0.081	0.054	0.134	0.056	0.042	0.177
SI 86 ~ SI 83	0.061	0.045	0.169	0.112	0.045	0.012
SI 83 ~ SI 80	0.143	0.041	<0.001	0.125	0.034	<0.001
SI 80 ~ SI 77	0.155	0.035	<0.001	0.162	0.033	<0.001
SI 77 ~ SI 74	0.118	0.034	0.001	0.173	0.030	<0.001
SI 74 ~ SI 71	0.137	0.033	<0.001	0.192	0.030	<0.001
SI 71 ~ SI 68	0.166	0.033	<0.001	0.166	0.030	<0.001
SI 68 ~ SI 65	0.094	0.034	0.005	0.144	0.030	<0.001
SI 65 ~ SI 62	0.136	0.033	<0.001	0.176	0.030	<0.001
SI 62 ~ SI 59	0.110	0.033	0.001	0.148	0.030	<0.001
SI 59 ~ SI 56	0.103	0.034	0.002	0.171	0.031	<0.001
SI 56 ~ SI 53	0.124	0.033	<0.001	0.147	0.032	<0.001
SI 53 ~ SI 50	0.094	0.038	0.012	0.170	0.035	<0.001
Cross-Lagged Regressions						
SI 89 ~ Poor SRH 86	0.160	0.036	<0.001	0.300	0.029	<0.001
SI 86 ~ Poor SRH 83	0.096	0.032	0.003	0.192	0.027	<0.001
SI 83 ~ Poor SRH 80	0.045	0.028	0.105	0.101	0.021	<0.001
SI 80 ~ Poor SRH 77	-0.012	0.024	0.623	0.060	0.020	0.003
SI 77 ~ Poor SRH 74	-0.010	0.022	0.666	0.011	0.019	0.541
SI 74 ~ Poor SRH 71	-0.010	0.023	0.651	-0.010	0.018	0.601
SI 71 ~ Poor SRH 68	-0.029	0.022	0.182	-0.018	0.018	0.338
SI 68 ~ Poor SRH 65	-0.011	0.023	0.648	-0.014	0.019	0.456
SI 65 ~ Poor SRH 62	-0.026	0.024	0.277	-0.019	0.019	0.334
SI 62 ~ Poor SRH 59	-0.008	0.025	0.744	-0.024	0.020	0.224
SI 59 ~ Poor SRH 56	0.005	0.026	0.832	-0.022	0.020	0.283
SI 56 ~ Poor SRH 53	0.004	0.026	0.873	-0.008	0.022	0.702
SI 53 ~ Poor SRH 50	0.013	0.030	0.669	-0.035	0.023	0.130
Poor SRH 89 ~ SI 86	-0.050	0.076	0.506	0.022	0.054	0.678
Poor SRH 86 ~ SI 83	-0.055	0.069	0.432	0.090	0.053	0.091
Poor SRH 83 ~ SI 80	-0.028	0.060	0.637	0.081	0.047	0.083
Poor SRH 80 ~ SI 77	-0.026	0.049	0.606	0.061	0.040	0.127
Poor SRH 77 ~ SI 74	-0.022	0.042	0.601	0.092	0.036	0.010
Poor SRH 74 ~ SI 71	-0.029	0.037	0.433	0.089	0.032	0.006
Poor SRH 71 ~ SI 68	-0.054	0.034	0.110	0.078	0.027	0.004
Poor SRH 68 ~ SI 65	-0.058	0.029	0.046	0.044	0.023	0.062

Poor SRH 65 ~ SI 62	-0.006	0.026	0.827	0.040	0.022	0.062
Poor SRH 62 ~ SI 59	0.038	0.024	0.104	0.067	0.020	0.001
Poor SRH 59 ~ SI 56	0.026	0.022	0.232	0.075	0.019	<0.001
Poor SRH 56 ~ SI 53	0.040	0.025	0.106	0.061	0.020	0.002
Poor SRH 53 ~ SI 50	0.031	0.031	0.304	0.090	0.024	<0.001
Intercept						
SI Intercept	1.336	0.075	<0.001	1.265	0.064	<0.001
Poor SRH Intercept	2.613	0.054	<0.001	2.528	0.044	<0.001
Poor SRH Slope	0.059	0.011	<0.001	0.039	0.009	<0.001
Mean						
SI 50	1.458	0.043	<0.001	1.333	0.037	<0.001
Covariances						
SI Intercept ~~ SI 50	0.586	0.057	<0.001	0.442	0.042	<0.001
SI Intercept ~~ Poor SRH Intercept	0.130	0.033	<0.001	0.186	0.024	<0.001
SI Intercept ~~ Poor SRH Slope	-0.018	0.005	0.001	-0.013	0.004	<0.001
Poor SRH Intercept ~~ Poor SRH Slope	0.002	0.005	0.677	-0.028	0.005	<0.001
SI_t ~~ Poor SRH_t (constrained to equal across $_t$)	0.026	0.006	<0.001	0.035	0.004	<0.001
Variances						
SI_t (constrained to equal across $_t$)	0.398	0.009	<0.001	0.389	0.007	<0.001
SI 50	1.090	0.070	<0.001	0.942	0.001	<0.001
Poor SRH_t (constrained to equal across $_t$)	0.453	0.008	<0.001	0.396	0.006	<0.001
SI Intercept	0.522	0.042	<0.001	0.436	0.034	<0.001
Poor SRH Intercept	0.714	0.033	<0.001	0.800	0.029	<0.001
Poor SRH Slope	0.003	0.001	0.002	0.004	0.001	<0.001
R-square						
SI 89	0.646			0.640		
SI 86	0.632			0.639		
SI 83	0.665			0.637		
SI 80	0.662			0.649		
SI 77	0.642			0.649		
SI 74	0.656			0.650		
SI 71	0.661			0.632		
SI 68	0.629			0.621		
SI 65	0.645			0.633		
SI 62	0.637			0.622		
SI 59	0.634			0.630		
SI 56	0.647			0.621		

SI 53	0.632	0.610
Poor SRH 89	0.611	0.646
Poor SRH 86	0.607	0.649
Poor SRH 83	0.602	0.639
Poor SRH 80	0.607	0.634
Poor SRH 77	0.602	0.645
Poor SRH 74	0.595	0.641
Poor SRH 71	0.595	0.642
Poor SRH 68	0.600	0.643
Poor SRH 65	0.614	0.658
Poor SRH 62	0.627	0.673
Poor SRH 59	0.636	0.686
Poor SRH 56	0.641	0.695
Poor SRH 53	0.649	0.701
Poor SRH 50	0.653	0.724

Notes: Full informational maximum likelihood was used to account for missing data. Models were run with robust maximum likelihood and controlled for race and educational attainment. Based on Model A, no constraints except model structure.
x^2 = 2052; DF = 772; BIC = -6794.24; CFI = 0.984; TLI = 0.977;
RMSEA = 0.008
SI = social isolation; SRH = self-rated health; t = 50-52, 53-55, 56-58, 59-61, 62-64, 65-67, 68-70, 71-73, 74-76, 77-79, 80-82, 83-85, 86-88, 89+

CONCLUSION

Social connections are critical for health and well-being as they can provide a range of informational, emotional, and instrumental resources that can lead to longer and healthier lives (Berkman and Syme 1979; Holt-Lunstad 2022; Holt-Lunstad et al. 2010; House et al. 1988; Snyder-Mackler et al. 2020). Those who are socially isolated, defined as an objective lack of social contact with others, cannot reap the benefits of social connections (Holt-Lunstad 2022; Holt-Lunstad and Steptoe 2022). To assess the scope and impact of social isolation, it is important to understand trends in isolation between and within-people over time, as well as how these trends relate to health. This dissertation advances research on social isolation by using multiple methods to examine social isolation across adulthood, across multiple axes of time, and by gender using two nationally representative longitudinal studies spanning from young adulthood to late life. Below, I offer key findings and takeaways from this dissertation followed by a discussion of its limitations and areas for future work.

First, my findings provide key insights into trends in social isolation by age, period, and cohort. I find that age trends in social isolation vary depending on whether population-based estimates or within-person changes are examined. Prevalence estimates from Chapter One show modest increases in social isolation across adulthood, with steep increases in late life. Meanwhile, within-person changes in social isolation, shown in Chapter Two, indicate that isolation is relatively stable within people as they age. This relative stability is due to both enduring (time-invariant) factors and recent history (lagged values). As discussed in Chapter Two, these differing age trends could be due to a variety of factors. There could be methodological differences, such as the estimation of lagged values which are difficult to capture in prevalence estimates as well as different age groupings across analyses, which could have led to these differing age trends. Additionally, there may be substantive reasons for these differences, such as changes in cohort composition, as well as societal or historical circumstances (Elder et al. 2003; Parigi and Henson 2014; Yang and Land 2013). Together, these age trends suggest the need for more research on social isolation earlier in the life course and for policies and programs addressing social isolation focused on older adults. Since social isolation is relatively stable in the within-person models I estimated across adulthood, it is important to examine trajectories of social isolation earlier in life, such as in adolescence or the transition to adulthood. Such research could provide additional insight into whether the enduring factors that influence isolation later in adulthood are more malleable earlier in life. Additionally, while there was no evidence for a distinct age trend in isolation after accounting for time-invariant and lagged values, prevalence estimates from Chapter One and health findings from Chapter Three indicate that older adults are particularly at-risk for social isolation.

Additionally, I find evidence for period and cohort differences in social isolation. Findings suggest that people in more recent birth cohorts and periods are more isolated than people in earlier birth cohorts and periods. Overall, increases in social isolation in more recent cohorts and periods are modest and not as high as what has been posited by Putnam (2000) and others (McPherson et al. 2006). Yet, increases in social isolation in both more recent cohorts and periods, even modest, alongside the lasting impacts of the COVID-19 pandemic, could indicate a greater burden of social isolation in the future. This suggests the need to develop a coordinated approach to address social isolation sooner rather than later (Murthy 2021).

Second, I find that social isolation and self-rated health are related in older adulthood but not in young adulthood or midlife. These findings have several substantive explanations and are supported by previous research. By midlife, individuals may already have established networks, leading to little change in isolation during this stage of the life course (Ertel et al. 2009). Additionally, during midlife, adults are often embedded in various social relationships including parental, child, and community connections (Lachman 2004; Yang et al. 2016), which may likewise demonstrate little change in isolation during this stage. It could also be that during midlife the quality of social relationships may be more important than the quantity of social relationships (Carmichael et al. 2015; Yang et al. 2016). Further research is also needed on other health outcomes to examine whether these patterns hold for different measures of health.

Results from Chapter Three imply that social isolation and self-rated health are reciprocally related in older adulthood. In particular, increases in social isolation are associated with worsening health in older adults, with the magnitude of this association remaining consistent from late midlife (age 50) to late life (ages 89+). This indicates a persisting effect of isolation on self-rated health. Additionally, I find that changes in self-rated health may only be related to changes in social isolation at later ages. While self-rated health may not have a substantial impact on isolation until later in life, it may also suggest that in the presence of large health declines, isolation is significantly impacted. Therefore, it is important to implement strategies that allow individuals with chronic conditions or declining health to remain socially connected. This can include addressing underlying issues such as hearing loss, accessibility to key resources, and knowledge of different communication technologies (National Academies of Sciences, Engineering, and Medicine 2020). Overall, these findings imply a need to focus resources on older adults to address isolation and limit health consequences in this vulnerable population.

Finally, this dissertation provides key insights on gender disparities in social isolation. While men are more isolated than women in young adulthood and midlife, this gender gap narrows in older adulthood and reverses in late life, with women becoming more isolated than men. This crossover is primarily due to large increases in the percentage of women not married or cohabitating in older adulthood, similar to findings by Umberson and colleagues (2022). However, when excluding relationship status from the social isolation index, men are more isolated than women at every age group. This implies that the measurement of social isolation is important to consider when examining gender disparities. Measurement differences could have led to inconsistent findings on the direction and magnitude of gender differences in isolation found in previous literature.

When examining gender differences in the relationship between social isolation and self-rated health, I find that the relationship is largely the same for men and women. However, in older adulthood women may experience more health risks from being socially isolated than men. These findings suggest the potential need to address isolation in older women. Given that women experience widowhood at higher rates than men (Mayol-García et al. 2021), which is the main factor leading to increases in isolation for older women, interventions for widowed women may be particularly beneficial.

These results indicate that overall, men may be more isolated than women, but women may experience greater health consequences from being isolated, as found in some previous literature (Hosseini et al. 2020, 2021; Röhr et al. 2021). However, a self-assessed measure of health may be tied to ideas of masculinity, leading men to rate their health better (Courtenay

2000). Examining more objective health measures could provide better insights into whether these gender differences are tied to physical health or psychological processes. While men may have fewer health risks associated with isolation, isolation can result in detriments in other areas. For example, isolation has been linked to political extremism, which may characterize men more so than women (Arendt 1973; Goldberg 2021; Linker 2021).

This dissertation is not without its limitations. Given that project-specific limitations are mentioned at the end of each chapter, here I overview broader limitations and areas for future research. First, I only examined social isolation at ages 25 and older. This is largely due to data and measurement limitations. Few nationally representative studies have examined social isolation within individuals at younger ages. Those that have are characterized by inconsistent measures of social isolation across survey waves. My dissertation proposal planned to use the National Longitudinal Study of Adolescent to Adult Health (Add Health) to examine social isolation from adolescence to young adulthood. However, upon further investigation of the data, I determined that measures of social isolation varied too much to evaluate trends over time. For example, frequency of contact with friends was not measured in all waves; thus, a measure of friend count would have needed to be used at one of the middle waves of Add Health. Social isolation increased dramatically during that wave (Wave IV), due to changes in this particular domain. Given the inconsistency in measurement, it was difficult to tell whether the increases in isolation were due to age, period, and/or cohort trends or measurement differences.

While Umberson et al. (2022) examined trajectories of social isolation in Add Health, the authors made some critical assumptions in measuring social isolation. In particular, some social relationship measures, such as friend count and volunteer activities, were not consistently measured across survey waves of Add Health, as mentioned above. Despite inconsistencies in measures of social isolation, the authors assessed trends over time, making it difficult to separate age-related change from change due to measurement. As such, I decided not to use Add Health in this dissertation and instead utilized the National Survey of Midlife Development in the United States (MIDUS) and the Health and Retirement Study (HRS).

Thus, more research is needed on social isolation earlier in the life course. Previous research finds that isolation is important during key developmental years of the life course, such as in adolescence and the transition to adulthood (Ertel et al. 2009; Hall-Lande et al. 2007; Hämmig 2019; Yang et al. 2016). Findings from this dissertation indicate the importance of time-invariant factors in assessing isolation in midlife and older adulthood. It is important to know whether there is more variation in social isolation and/or greater health impacts of isolation earlier in the life course. However, more data and consistent measurement are needed to address these questions.

Second, since there is no gold standard for measuring social isolation, studies have used a variety of measurement strategies based on the data available and the population examined. I chose a modified version of the Berkman-Syme Social Network Index (BSNI; Berkman and Breslow 1983) for a variety of reasons including its underlying theoretical framework, strong associations with health, and usability in clinical and research settings. However, this measure has its limitations, such as the dichotomization of social ties (see the Limitations section in Chapter One for a broader discussion of the strengths and weaknesses of this measure). A consistent measurement tool that applies to a variety of ages and population groups is needed to compare the trends and impacts of isolation across studies. An updated measure of social isolation should incorporate more domains and aspects, such as digital communication and workplace connections.

Third, I only examined gender differences due to data limitations and to keep the project manageable. Thus, future research must examine social isolation among other groups, such as by race/ethnicity, socioeconomic status, geography, disability status, and in LGBTQ+ populations. Research is emergent in this area, but more is needed to assess trends and develop strategies to reduce isolation in these populations (Fredriksen-Goldsen et al. 2013; Naito et al. 2021; Taylor et al. 2022, 2019). The methodology used in this dissertation can be used to study trends in these populations.

Fourth, this dissertation largely focused on trends and health impacts of isolation. Future work should investigate mechanisms behind these relationships as well as potential programs and policies to address isolation. Mechanisms can help determine why gender differences in social isolation exist, why isolation endures across adulthood, and how increases in isolation lead to changes in self-rated health in older adulthood. While this dissertation uses theory and previous research to speculate why these findings may be occurring (Carstensen 1993; Cornwell et al. 2008; Elder 1998; Kobayashi and Steptoe 2018; Mayol-García et al. 2021; Umberson et al. 2022; Vandervoort 2000), more research is needed to confirm these explanations. Additionally, evidence-based policies and programs need to be developed to address social isolation. Some recommendations have focused on individual behavior change, such as starting a hobby or volunteering (National Institute on Aging 2021). However, structural solutions with community-based designs are needed to better address social isolation (Holt-Lunstad 2020a, 2022). As calls for programs and policies to address social isolation have increased as a result of the COVID-19 pandemic, solutions must be developed with this structural framework in mind to help address underlying causes of isolation (Holt-Lunstad 2020b; Murthy 2021).

While social isolation was a public health issue before the pandemic, the pandemic has exacerbated this issue (Holt-Lunstad 2020b; Holt-Lunstad and Perissinotto 2022). Research should continue to evaluate trends in social isolation to assess whether isolation has remained at peak-pandemic levels or has declined. It may be particularly important to examine how the pandemic has impacted adolescents and older adults, who were particularly affected by social distancing guidelines. For example, physical isolation from peers during a key developmental stage of the life course, such as adolescence, may have led to lasting impacts on levels of social isolation and mental health (Hu et al. 2022; Loades et al. 2020; Na et al. 2022). Additionally, the pandemic may have led to increased isolation in older adults, which as this dissertation found is a group already at heightened risk of isolation. These topics should be explored in the coming years.

In sum, this dissertation helps advance the understanding of social isolation across the adult life course in the United States. I expand on findings from previous research by examining trends in social isolation between and within-people across the adult life course, investigating the reciprocal relationship between social isolation and health, and exploring gender differences. Overall, findings suggest that older adults are particularly vulnerable to social isolation. Not only does this population have the highest rates of isolation, but they also experience the greatest health consequences of isolation. Given the aging of the U.S. population, the increase in isolation among younger cohorts, and the acceleration of these trends during the pandemic, isolation is likely to increase in the coming years (Holt-Lunstad and Perissinotto 2022; Peng and Roth 2022; Quintana et al. 2021). This indicates the need for resources to address this future burden. I also find that within-person changes in isolation are largely predicted by enduring aspects and recent history. Therefore, research should examine isolation earlier in the life course to determine early life factors which may affect trajectories of isolation. Last, results on gender differences suggest that it is important to consider how isolation is measured when assessing differences across population groups. Yet, findings largely suggest that resources are needed in early life to increase the connectedness of men, while in older adulthood additional support may be needed for women, particularly those who are widowed.

While this dissertation expands the literature on social isolation, we must continue this line of research, particularly given the strains of social isolation experienced by millions of people during the pandemic (Birditt et al. 2021; Holt-Lunstad 2020b; O'Sullivan, Burns, et al. 2021). While scholars have long identified social isolation as a significant risk factor for poor health outcomes (Berkman and Syme 1979; House et al. 1988; Umberson and Montez 2010), this has become more visible to the public, policymakers, and health practitioners during the pandemic. This increased attention should be used to devote resources to evidence-based policies and programs that foster social connection across the life course, particularly among vulnerable populations.

APPENDIX 1: DEFINITIONS OF SOCIAL ISOLATION AND LONELINESS

Definitions (National Academies of Sciences, Engineering, and Medicine, 2020: 28)

Social isolation: the objective lack of (or limited) social contact with others

Loneliness: the perception of social isolation or the subjective feeling of being lonely

APPENDIX 2: CHAPTER 2 SUPPLEMENTAL TABLES

Appendix Table 2.1A. Comparison of fit statistics for models not controlling for race and educational attainment, the National Survey of Midlife Development in the United States, 1995-2014 (N = 3,027)

Model	x^2	DF	BIC	CFI	TLI	RMSEA
Latent Time-Invariant	218.16	87	-535.88	0.928	0.945	0.019
Autoregressive (AR Constrained)	249.35	75	-428.86	0.910	0.921	0.023
Autoregressive	246.98	65	-355.30	0.909	0.908	0.025
Linear Growth Curve	203.83	84	-523.32	0.934	0.948	0.019
ALT Intercept Only (AR Constrained)	143.74	83	-561.70	0.967	0.974	0.013
ALT Intercept Only	108.00	73	-514.03	0.983	0.984	0.010

Notes: Full informational maximum likelihood was used to account for missing data. Models were run with robust maximum likelihood and social isolation variances were constrained to equal by age. ALT Growth Model did not converge. AR = autoregressive equation, ALT = autoregressive latent trajectory.

Appendix Table 2.1B. Comparison of fit statistics for models not controlling for race and educational attainment, Health and Retirement Study, 2006-2016 (N = 24,564)

Model	x^2	DF	BIC	CFI	TLI	RMSEA
Latent Time-Invariant	2764.85	116	590.94	0.901	0.922	0.024
Autoregressive (AR Constrained)	3214.57	103	835.50	0.893	0.906	0.027
Autoregressive	3203.68	91	816.11	0.901	0.901	0.027
Linear Growth Curve	1622.23	113	-115.75	0.944	0.955	0.019
ALT Intercept Only (AR Constrained)	2543.52	112	437.09	0.912	0.928	0.023
ALT Intercept Only	1183.86	100	-347.82	0.964	0.967	0.016

Notes: Full informational maximum likelihood was used to account for missing data. Models were run with robust maximum likelihood and social isolation variances were constrained to equal by age. ALT Growth Model did not converge. AR = autoregressive equation, ALT = autoregressive latent trajectory.

Appendix Table 2.2A. Comparison of fit statistics for models adding controls for gender and cohort, the National Survey of Midlife Development in the United States, 1995-2014 (N = 3,052)

Model	x2	DF	BIC	CFI	TLI	RMSEA
Latent Time-Invariant	163.74	87	-581.85	0.964	0.934	0.014
Autoregressive (AR Constrained)	252.02	75	-438.96	0.925	0.838	0.022
Autoregressive	255.13	65	-363.95	0.923	0.808	0.024
Linear Growth Curve	145.30	84	-569.89	0.971	0.944	0.013
ALT Intercept Only (AR Constrained)	130.53	91	-638.84	0.982	0.968	0.010
ALT Intercept Only	143.94	81	-555.22	0.973	0.946	0.013

Notes: Full informational maximum likelihood was used to account for missing data. Models were run with robust maximum likelihood, controlled for race and educational attainment, and social isolation variances were constrained to equal by age. ALT Growth Model did not converge. AR = autoregressive equation, ALT = autoregressive latent trajectory.

Appendix Table 2.2B. Comparison of fit statistics for models adding direct controls for gender and cohort, Health and Retirement Study, 2006-2016 (N = 24,501)

Model	x2	DF	BIC	CFI	TLI	RMSEA
Latent Time-Invariant	845.76	116	-654.42	0.976	0.958	0.013
Autoregressive (AR Constrained)	3530.70	103	808.70	0.903	0.808	0.027
Autoregressive	3799.63	91	789.11	0.910	0.799	0.027
Linear Growth Curve	-	-	-	-	-	-
ALT Intercept Only (AR Constrained)	805.96	120	-712.70	0.977	0.961	0.012
ALT Intercept Only	794.78	108	-625.20	0.978	0.959	0.012

Notes: Full informational maximum likelihood were used to account for missing data. Models were run with robust maximum likelihood, controlled for race and education, and error variance were constrained to equal. ALT Growth Model and Linear Growth Curve Model did not converge. AR = autoregressive equation, ALT = autoregressive latent trajectory.

Appendix Table 2.3A. Select parameter estimates from the Linear Growth Curve Model, National Survey of Midlife Development in the United States, 1995-2014 (N = 3,052)

Parameter	Estimate	Std. Err.	P-value
Intercept			
Intercept	0.828	0.106	<0.001
Slope	0.007	0.009	0.457
Covariances			
Intercept ~~ Slope	-0.013	0.008	0.121
Variances			
SI_t (constrained to equal across $_t$)	0.368	0.014	<0.001
Intercept	0.523	0.049	<0.001
Slope	0.004	0.002	0.014
R-square			
SI 80	0.679		
SI 75	0.660		
SI 70	0.638		
SI 65	0.617		
SI 60	0.610		
SI 55	0.600		
SI 50	0.600		
SI 45	0.608		
SI 40	0.598		
SI 35	0.600		
SI 30	0.596		
SI 25	0.596		

Notes: Full informational maximum likelihood was used to account for missing data. Models were run with robust maximum likelihood and controlled for race and educational attainment.
x2 = 133; DF = 84; BIC = -574.53; CFI = 0.975; TLI = 0.959; RMSEA = 0.012
SI = social isolation; t = 25-29, 30-34, 35-39, 40-44, 45-49, 50-54, 55-59, 60-64, 65-69, 70-74, 75-79, 80+

Appendix Table 2.3B. Select parameter estimates from the Linear Growth Curve Model, Health and Retirement Study, 2006-2016 (N = 24,537)

Parameter	Estimate	Std. Err.	P-value
Intercept			
Intercept	1.351	0.019	<0.001
Slope	0.033	0.003	<0.001
Covariances			
Intercept ~~ Slope	0.001	0.003	0.804
Variances			
SI_t (constrained to equal across $_t$)	0.373	0.004	<0.001
Intercept	0.656	0.019	<0.001
Slope	0.000	0.001	0.541
R-square			
SI 89	0.686		
SI 86	0.672		
SI 83	0.672		
SI 80	0.670		
SI 77	0.667		
SI 74	0.667		
SI 71	0.661		
SI 68	0.657		
SI 65	0.654		
SI 62	0.653		
SI 59	0.650		
SI 56	0.652		
SI 53	0.650		
SI 50	0.651		

Notes: Full informational maximum likelihood was used to account for missing data. Models were run with robust maximum likelihood and controlled for race. Model only converged with education covariates.

x2 = 936; DF = 113; BIC = -548.40; CFI = 0.971; TLI = 0.966; RMSEA = 0.014
SI = social isolation; t = 50-52, 53-55, 56-58, 59-61, 62-64, 65-67, 68-70, 71-73, 74-76, 77-79, 80-82, 83-85, 86-88, 89+

Appendix Table 2.4A. Select parameter estimates from the Autoregressive Latent Trajectory Intercept Only Model without covariates, National Survey of Midlife Development in the United States, 1995-2014 (N = 3,027)

Parameter	Estimate	Std. Err.	P-value
Autoregressives (with all coefficients equal)			
$SI_t \sim SI_{t-1}$	0.293	0.076	<0.001
Intercept			
Latent time-invariant	0.889	0.097	<0.001
Mean			
SI 25	1.430	0.054	<0.001
Covariances			
Intercept ~~ SI 25	0.179	0.052	0.001
Variances			
SI_t (constrained to equal across $_t$)	0.390	0.013	<0.001
SI 25	0.813	0.055	<0.001
Intercept	0.265	0.065	<0.001
R-square			
SI 80	0.592		
SI 75	0.592		
SI 70	0.592		
SI 65	0.592		
SI 60	0.592		
SI 55	0.592		
SI 50	0.592		
SI 45	0.591		
SI 40	0.587		
SI 35	0.573		
SI 30	0.530		

Notes: Full informational maximum likelihood was used to account for missing data. Models were run with robust maximum likelihood.

x^2 = 144; DF = 83; BIC = -561.70; CFI = 0.967; TLI = 0.974; RMSEA = 0.013

SI = social isolation; t = 30-34, 35-39, 40-44, 45-49, 50-54, 55-59, 60-64, 65-69, 70-74, 75-79, 80+

Appendix Table 2.4B. Select parameter estimates from the Autoregressive Latent Trajectory Intercept Only Model without covariates, Health and Retirement Study, 2006-2016 (N = 24,564)

Parameter	Estimate	Std. Err.	P-value
Autoregressives			
SI 89 ~ SI 86	0.447	0.021	<0.001
SI 86 ~ SI 83	0.332	0.021	<0.001
SI 83 ~ SI 80	0.269	0.021	<0.001
SI 80 ~ SI 77	0.244	0.021	<0.001
SI 77 ~ SI 74	0.182	0.021	<0.001
SI 74 ~ SI 71	0.164	0.021	<0.001
SI 71 ~ SI 68	0.146	0.021	<0.001
SI 68 ~ SI 65	0.109	0.021	<0.001
SI 65 ~ SI 62	0.130	0.021	<0.001
SI 62 ~ SI 59	0.133	0.020	<0.001
SI 59 ~ SI 56	0.134	0.021	<0.001
SI 56 ~ SI 53	0.137	0.021	<0.001
SI 53 ~ SI 50	0.106	0.022	<0.001
Intercept			
Latent time-invariant	1.258	0.029	<0.001
Mean			
SI 50	1.384	0.027	<0.001
Covariances			
Intercept ~~ SI 50	0.571	0.029	<0.001
Variances			
SI_t (constrained to equal across $_t$)	0.407	0.006	<0.001
SI 50	1.035	0.041	<0.001
Intercept	0.474	0.027	<0.001
R-square			
SI 89	0.771		
SI 86	0.719		
SI 83	0.687		
SI 80	0.669		
SI 77	0.637		
SI 74	0.627		
SI 71	0.615		
SI 68	0.598		
SI 65	0.609		
SI 62	0.610		
SI 59	0.611		
SI 56	0.611		
SI 53	0.598		

Notes: Full informational maximum likelihood was used to account for missing data. Models were run with robust maximum likelihood.
$x^2 = 1184$ DF = 100; BIC = -347.82; CFI = 0.964; TLI = 0.967; RMSEA = 0.016
SI = social isolation; t = 53-55, 56-58, 59-61, 62-64, 65-67, 68-70, 71-73, 74-76, 77-79, 80-82, 83-85, 86-88, 89+

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